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PRODUCTIVITY GROWTH OF US STATES

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Economics

by
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Dedicated to Maa Vaishno Devi and my parents.

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Table of Contents

Abstract

This dissertation makes a contribution to regional studies by constructing Multi-Factor Productivity (MFP) growth measures at the state level for the US. The first essay of the dissertation exploits a dual growth accounting technique to calculate sector-specific MFP growth for all US states from 1980 onwards. In the process, the essay contributes by constructing a data set on the state level real user cost of capital paying particular attention to inter-state variations in the composition of output, relative prices of investment goods, effective corporate taxes, and inflation rates for the manufacturing and service sectors. Some of the key implications of our analysis are: a) The contribution of MFP growth in driving labor productivity is higher in the manufacturing sector compared to the service sector; b) The source of divergence between the primal and dual measures of MFP growth originates from inconsistencies between the constructed real user cost and the implied real user cost of Bureau of Economic Analysis; c) The real user cost for the service sector demonstrates negative growth rate resulting from a rapid decline in the relative price ratio of investment goods providing support for "Investment Specific Technological Change" and also implying high rates of capital accumulation; d) The average growth in the real user cost of capital is non-zero and shows wide variability across states for both the sectors.

The primary focus of the second essay is to capture the positive impacts of schooling and Research and Development (R&D) expenditure on MFP growth for US states. While the evidence for positive externalities from schooling has been disappointing in the regional literature, the evidence of externalities from R&D is seldom found at the state level in US. The essay argues that a state with higher level of education not only creates better ideas, but also is more favorable to adopt, implement and execute the newly available ideas and hence, to absorb the knowledge spillovers. Further, it is argued that the states with favorable R&D

policies attract more efficient firms and hence, experience higher MFP growth. To achieve this, the essay extends the dual accounting exercise to construct MFP growth measures for the non-farm, non-mining, private sector for all US states and successfully establishes the superiority of the dual measures. The empirical exercise documents significant positive externalities from schooling and R&D only after controlling the "catch-up" effect where poor states converge towards the rich states and attributes an important role to schooling and R&D in speeding up this process.

Chapter 1

Introduction

Historically, researchers working on economic growth have attributed a significant role to the multi-factor productivity (MFP) growth in driving labor productivity.[1] In the last two decades, the confidence in this finding is supported by empirical evidence drawn from developing countries.[2] The last two decades has also witnessed substantial consensus in the dominant contribution of MFP growth in explaining pattern of labor productivity growth in US.[3] However, the corresponding literature is limited at the regional level in US, and instead, most of the regional literature has assumed MFP growth to be similar across the states.[4] The argument for differing productivity growth or MFP growth across states can at least be supported in the presence of a varying industry mix. Some of the existing literature which assumes productivity growth to be different across states apportions the industry specific Bureau of Economic Analysis (BEA) capital stock data to the states based on the income share of each state to construct the measures of MFP growth (Turner et.al., 2008). This method of apportioning relies on the assumption of equalization of marginal product of capital across states. This assumption is questionable in the presence of inter-industry compositional differences across states and differences in the state tax policies. Further, the difficulty in measuring the national stock of physical capital is widely acknowledged among economists and the evidence of measurement errors in the capital stock is well documented in the cross-country literature (Hsieh, 1999, 2002). This dissertation makes a contribution

[1]See Solow (1957), Denison (1962, 1967)
[2]See King and Levine (1994), Klenow and Rodriguez-Clare (1997)
[3]See Gordon (2000), Steindel and Stiroh (2001) and Jorgenson et.al. (2008)
[4]See Barro and Sala-i-Martin (1991, 1992) and Garofalo and Yamarik (2002)

to the regional literature by constructing productivity growth measures at the state level for different sectors by utilizing the alternative dual accounting method. The unique advantage of this approach is that it relies on the real factor price data which is directly observable. The foundation to this approach is laid on the notion that any growth to productivity is reflected in growth of the real factor prices. Further, the dissertation also makes an important contribution by exploring the link between the constructed measures and its determinants, schooling and Research and Development (R&D) expenditure.

After discussing the literature on MFP growth in the second chapter, this dissertation undertakes a dual accounting exercise in the third chapter to construct the productivity growth measures for the manufacturing and service sectors for the US states. This exercise is particularly interesting given that both sectors experienced different productivity growth patterns during the famous productivity slowdown of 1973-95. While manufacturing industries experienced higher productivity growth, the service sector displayed minimal growth during this period.[5] Further, the huge literature devoted to it at the national level provides us an opportunity to compare and validate our results. In the process of constructing the measures of MFP growth, this chapter makes an important contribution by developing a state level data set on the real user cost of capital for the manufacturing and service sectors taking into account inter-state variations in the industrial composition of state output, the relative price of investment goods, effective corporate income taxes and inflation rates. Our empirical exercise finds that MFP growth is associated positively with labor productivity growth for both sectors with the manufacturing sector experiencing a stronger association. Similarly, we find variations in MFP growth across states to play a much larger role in explaining the disparity in labor productivity growth across states in manufacturing sector than in services. This finding is in accordance with the existing literature which provides evidence of varying productivity growth patterns for both sectors. Further, to substantiate our measures, we compare our national measure of MFP growth with the measures obtained from the standard/primal growth accounting exercise utilizing the Bureau of Economic Analysis (BEA) data set on the physical capital stock and the labor force. Unlike

[5]See Triplett and Bosworth (2001) and Jorgenson et.al. (2005)

our measures, the BEA measures fail to generate patterns similar to those documented in the existing literature, and we find our measures to differ substantially from those obtained from the BEA data set with services experiencing the maximum divergence. The empirical analysis pins down this divergence to inconsistencies between our constructed real user cost and the implied real user cost of BEA. While both the constructed and implied real user cost of capital depict positive trends for the manufacturing sector, they display the opposite pattern for services with the constructed measure displaying a negative trend. The negative growth in the real user cost originates from a rapidly falling ratio of the price of investment goods relative to the state output deflator which provides evidence of "Investment Specific Technological Change".[6] This implies a much higher growth rate of the physical capital stock compared to that obtained from BEA. This questions the approximation of BEA capital stock to the states to conduct the growth accounting exercise. Finally, the empirical exercise finds wide variability of the real user cost of capital across states and concludes that the standard practice of approximating MFP growth by real wage growth to be unwarranted.

The fourth chapter of the dissertation extends the accounting framework to construct the cross-state productivity growth measures for the non-farm, non-mining private sector. Similar to the previous chapter, our productivity growth measures successfully emulate the patterns established by the literature on the productivity slowdown. Further, the empirical exercise identifies a positive association between productivity growth and two of its major determinants, schooling and R&D. Any evidence of such positive associations (externalities) has clear implications in shaping state policies in promoting education and R&D. It can be argued that a state with a higher level of education not only creates better ideas, but also is better able to adopt, implement and execute the newly available ideas and hence, to absorb the knowledge spillovers. However, the evidence from regional studies is not robust in documenting such externalities from education in US.[7] At the same time, the studies identifying R&D externalities are seldom found at the regional level in US. A case for R&D externalities can be made where a state with favorable R&D policies displays

[6]See Greenwood et.al. (1997)

[7]See Acemoglu and Angrist (2001), Ciccone and Peri (2006)

higher productivity growth by attracting more efficient firms. The empirical exercise provides evidence of positive externalities from schooling and R&D once we control for the poor states catching up to the rich states in the spirit of Nelson and Phelps (1966) and Benhabib and Spiegel (1994, 2005). This attributes an important role to schooling and R&D expenditure in closing the gap between the rich and the poor states, hence speeding up technological diffusion. The final chapter of the dissertation provides concluding remarks.

Chapter 2

Literature Review

2.1 Background

Why does income per capita vary so much across developed and less developed countries? In Pritchett's (1997) words, there is "divergence, big time". In his study, he finds a five fold increase in the per capita income of the richest countries relative to the poorest ones between 1870 and 1990. While developed nations have experienced steady and rapid growth rates in per capita income, the majority of the developing and underdeveloped nations have displayed very slow growth rates which have intensified this disparity in per capita income. Historically, growth economists have addressed this issue of disparity by focusing on the importance of factor accumulation relative to Total Factor Productivity (TFP), otherwise known as Multi-Factor Productivity (MFP).

The literature focusing on factor accumulation especially analyzes the role played by physical capital accumulation in driving economic growth. This literature, otherwise termed as "Capital Fundamentalism" strongly acknowledges the role of investment in physical capital as a fundamental cause of economic growth.[1] The classic growth models by Harrod (1939) and Domar (1946) form the basis of this argument which was further substantiated by proponents like Arthur Lewis (1954) and W.W. Rostow (1960). On the contrary, the proponents of MFP attribute a substantial importance to it in explaining the cross country

[1] The reader can also refer to King and Levine (1994) for an excellent review on the importance of capital fundamentalism and productivity. This section briefly reviews some of the facts documented in King and Levine (1994).

disparity in income per capita and its growth (Solow, 1957 and Denison, 1962, 1967).[2] Utilizing a growth accounting framework developed by Solow (1957), Denison (1962, 1967) found that factor accumulation accounts for a smaller portion of labor productivity growth for the nine developed nations. Similarly in a development accounting exercise, Denison (1962, 1967) did not find evidence of variation in capital per worker contributing substantially in explaining the cross-country variation in output per worker. The evidences from Denison (1962, 1967) diminishes the view of "Capital Fundamentalism" in explaining the cross country income disparity. With the availability of Summers and Heston's (1988) cross country data set, economists have extended the empirical exercises to many developing nations to factor out the relative importance of factor accumulation to MFP.

In the late 20th century, the literature focusing on "Capital Fundamentalism" was further reinforced by Mankiw, Romer and Weil (1992) and Young (1995) who provided substantial evidence on the role of physical and human capital accumulation in explaining the cross country disparity in income per capita and economic growth. Mankiw, Romer and Weil (1992) (henceforth, MRW) empirically extended the neoclassical growth framework proposed by Solow (1956) to a large cross section of developing countries utilizing the Summers and Heston (1988) data set. In Solow's framework, a country's steady state level of income varies positively with its saving rate which determines the capital accumulation of the country, and inversely with the population growth rate. In MRW's empirical exercise, the saving rate and population growth rate enter with the expected signs in the cross country regressions and account for more than 50% of the cross-country variations in per capita income. Further, the authors augment the neoclassical growth framework by introducing human capital. With the introduction of human capital, the model explains 80% of the cross country variations in per capita income which further substantiated the importance of factor accumulation in explaining the cross country income disparity. To address the much debated issue of divergence in income per capita across countries, MRW assert that in the neoclassical growth framework each country converges towards a different steady-state level and it would be

[2]The paper by King and Levine (1994) presents a detailed review on the findings by Solow (1957) and Denison (1962, 1967). This section briefly outlines those findings reported in King and Levine (1994).

difficult to document the evidence of convergence if not accounting for the country specific determinants of the steady state income level, i.e. the saving rate, growth rate of population and human capital. The conditional convergence framework proposed by the authors provides evidence of convergence in income per capita across countries conditioned on the steady state income determinants.

Young (1995) further strengthened this strand by attributing the miraculous growth experience of the East Asian tigers to factor accumulation. The per capita income for these newly industrialized economies: Hong Kong, Singapore, South Korea and Taiwan experienced extraordinary growth rates between 5.7%-6.8% for 1966-1990. Young (1995) attributed the extraordinary growth rates to rising labor force participation rate especially for women, increasing educational attainment of the labor force and capital deepening which minimized the contribution of the residual MFP growth. Among these four countries, Hong Kong and Taiwan experienced comparatively higher annual MFP growth rates of 2.3% and 2.6% respectively. Hong Kong did not experience a rapid capital deepening as the investment to GDP ratio remained stable and the composition adjusted labor input experienced a marginally higher growth rate. These two factors did not depress the MFP growth substantially. On the contrary, though Taiwan experienced a rapid capital deepening resulting from a higher investment to GDP ratio, a relatively lower labor input growth generated a MFP growth rate of 2.6%. Capital deepening for South Korea was remarkable between 1966-1990 with investment rates experiencing a two fold increase between late 1960s and 1991. With this rapid capital accumulation, the output per effective capital fell at the rate of 3.4% annually. However, the output per effective labor displayed a comparatively higher growth rate of 3.9% with output growing relatively faster than the adjusted labor input. These two forces along with a very high labor income share generated a MFP growth rate of 1.7% for South Korea. Similarly, capital deepening featured prominently for Singapore with the investment to GDP ratio experiencing an almost five fold increase between 1960-1984 generating a negative growth rate in output per effective capital. Further, rapidly rising labor force participation rate did not add much to the growth of output per effective labor. The residual MFP experienced a marginal growth rate of 0.2%, the lowest among the four countries. In a cross country comparison, Young (1995) asserted that though the East Asian economies experienced remarkable output growth, their MFP growth was very similar to the productivity growth documented across nations. So, he attributed this growth experience of the East Asian tigers to factor accumulation such as rapid capital deepening, rising labor force participation, educational attainment and an intersectoral transfer of laborers from agriculture to manufacturing.

As per our earlier discussion, growth proponents like Solow (1957) and Denison (1962, 1967) attributed a significant importance to MFP in explaining the cross country disparity in income per capita and its growth. However, the development economists were hesitant to accept these views as the inferences were drawn only from the developed nations. The last two decades has witnessed an enormous evidence both from developed and developing nations regarding the contribution of MFP. This chapter introduces the reader to this literature on MFP growth in the subsequent sections. The rest of the chapter is structured as follows: section (2.2) documents the importance of MFP growth by furnishing evidence from the developing countries. Section (2.3) summarizes the evidence available from dual growth accounting. Section (2.4) reviews the literature related to the growth experience of USA. Section (2.5) summarizes the literature available at the state level and section (2.6) concludes.

2.2 Reemergence of Multi-Factor Productivity

Though the evidence from the industrialized nations widely acknowledges the importance of MFP in explaining the variations in per capita income and its growth, studies related to developing countries were scarce due to the lack of data on developing economies. The last decade of the twentieth century has witnessed a considerable amount of research focusing on the importance of MFP for the developing nations with the availability of data set developed by Summers and Heston (1988, 1991). This section briefly documents this evidence by discussing three classic papers: King and Levine (1994), Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999).

King and Levine (1994) construct measures of physical capital stock for a large cross section of countries including both developed and developing nations and extend the development and growth accounting exercises to draw inference about capital fundamentalism. They find a very strong positive association between the capital-output ratio and income per capita. Their finding suggests that while a country similar to the US in per capita income experiences a capital-output ratio of 3.1, a country with a very low per capita income relative to the US depicts a capital-output ratio of 1.4. In a development accounting exercise, the authors find that physical capital accounts for 43%-59% of the variation in per capita income contrary to the reported 25% by Denison (1967). However, on a cautionary note the authors assert that this substantial variation accounted by physical capital results from the assumption of a high capital income share of 0.4 which is mostly applicable to the developed nations. Additionally, reducing the capital income share to 0.25 as in Denison (1967) reduces the contribution of physical capital stock to a moderate 28%-44% in explaining the variations in income per capita. However, the inference drawn from the growth accounting is very similar to Denison (1967) where the per capita capital growth rate contributes little (around 40%) to the per capita income growth across countries. This is suggestive of the importance of the MFP growth in driving the cross country per capita income growth.

In a classic paper, Klenow and Rodriguez-Clare (1997) address the empirical conclusion presented by MRW and Young (1995) which reinforces the importance of factor accumulation in explaining the cross country variation in income per capita and its growth. The authors develop a variance decomposition approach to attribute the variations in labor productivity to factor accumulation and productivity. Klenow and Rodriguez-Clare (1997) succeed in replicating the results of MRW where variations in factor inputs account for 78% of the variations in labor productivity. The authors update the existing measure of human capital representing the secondary schooling enrollment rate by adding data on the primary and tertiary schooling enrollment rates. As the primary enrollment rates display less variation across the countries, this new measure of human capital reduces the contribution of factor inputs to a mere 40% in explaining the cross-country variations in labor productivity. Further, Klenow and Rodriguez-Clare (1997) argue the human capital production to be more labor intensive contrary to the specification of MRW. Utilization of a labor intensive production technology for human capital further reduces the contribution of factor inputs to 33%, which implies a 67% contribution of the productivity in explaining the variations in labor productivity. To incorporate experience and schooling quality to the measure of human capital, the authors make use of cross country Mincerian wage regressions. With these updates to the measure of human capital, variations accounted by the factor inputs reduce to approximately 50% or less than that which is not as robust as claimed by MRW. Klenow and Rodriguez-Clare (1997) conclude that the secondary enrollment rate as a measure of human capital overstates the variations accounted to factor accumulation as other measures of human capital do not experience such wide cross country variations as depicted by the secondary enrollment rate. Similarly, in a growth accounting exercise, the authors also conclude the variations in the MFP growth to account for majority of the variations in the labor productivity growth.

Hall and Jones (1999) first pin down the proximate causes of the disparity in labor productivity and then link it to the social infrastructure which is the fundamental source to foster labor productivity. In a development accounting framework, the authors decompose the variations in labor productivity across countries into variations in the capital to output ratio, human capital per worker and productivity levels. Utilizing the data on 127 countries, the authors find that for the year 1988, the top five countries with the highest labor productivity experience a 31.7 fold higher labor productivity compared to the bottom five. The empirical findings suggest that the differences in capital to output ratio and human capital per worker account for factors of only 1.8 and 2.2 respectively, where as the differences in MFP levels account for a substantial factor of 8.3. Additionally, the authors predict only a four fold disparity in labor productivity between the top and bottom five countries in absence of this substantial MFP differences. This conclusion refutes the earlier view of variation in factor intensity accounting for the substantial variation in labor productivity. Further, the authors explain that the average investment rates and educational attainments vary moderately by a factor 2.9 and 8.1 years respectively between the top and the bottom five countries. This moderate variation along with a smaller income share of capital (1/3) account marginally for the differences in labor productivity. Hall and Jones (1999) question the assumption of independence of the MFP and the factor intensities made by MRW. On the contrary, they provide evidence of high correlation between the two. Citing Parente and Prescott (1999), the authors explain that this enormous cross country productivity difference is highly plausible in the presence of barriers to technological adoption and secondly, in the presence of adverse social infrastructure. Social infrastructure represents institutions and government polices which create a conducive environment to promote factor accumulation and technological adoption. The authors find a very strong association between the measure of social infrastructure and labor productivity and strongly attribute the differences in labor productivity to the differences in social infrastructure.

The evidence presented from a large cross section of developing economies in this section clearly identifies with the view presented by Solow (1957) and Denison (1962, 1967) where MFP contributes extensively in explaining the cross country disparity in income per capita and its growth. Till now, the discussion has been centered around development and growth accounting which relies on data sets of output and factor inputs to back out MFP and its growth respectively. In the following section, we represent the evidence from an alternative dual accounting method which relies on the real factor prices to further substantiate the importance of MFP growth.

2.3 Evidence from Dual Growth Accounting

The difficulty in measuring the stock of physical capital is widely acknowledged among economists and in the presence of measurement errors, the reliability of the results from standard growth accounting exercise is questionable. Therefore, dual growth accounting which relies on the observed factor prices strongly complements and acts as a tool to corroborate or to challenge the findings from standard growth accounting exercises. This approach of measuring MFP growth using the observed real factor price growth extends at least back to Jorgenson and Griliches (1967). This approach is based on the fact that any growth to MFP which causes output to grow would also cause real factor prices to grow due to increases in the marginal product of the factors. MFP growth can then be measured as the weighted average of the growth rates of the real factor prices i.e. the real wage and the real user cost. This section briefly documents the papers by Hsieh (2002) and Aiyar and Daalgard (2005) to provide evidence from the dual growth accounting exercises.

Hsieh (2002) challenges the earlier finding of attributing the miraculous growth experience of the East Asian countries to factor accumulation. The author argues that in the presence of a constant capital income share, a rapid increase in capital to output ratio resulting from a very high accumulation of physical capital stock would lead to a similar decline in the marginal product of capital. The data from national accounts suggests a remarkable increase in the capital to output ratio for Korea and Singapore at the annual rate of 3.4% and 2.8% respectively. Though Hsieh finds evidence of a similar decline in the marginal product of capital for South Korea from the observed measures in the factor market, he fails to document a similar decline for Singapore which is suggestive of overestimation of the physical capital stock by national accounts of Singapore. In the presence of such overestimation, the standard growth accounting results would yield biased measures for MFP growth. So, Hsieh exploits the dual growth accounting approach which relies on observed real factor prices where the MFP growth is measured as a weighted average of the growth rates of real wage and real user cost. Hsieh further argues that both standard growth accounting and dual accounting would yield similar results if the observed factor prices are consistent with the national accounts data. To carry out dual growth accounting, the author constructs the measures of real wage growth and real user cost growth for South Korea, Singapore, Taiwan and Hong Kong. The measure of real wage growth undergoes a quality adjustment based on four educational categories and sex. The aggregate real user cost growth undergoes a similar quality adjustment based on five categories of capital goods: residential building, non-residential buildings, other construction, transport equipment and machinery equipment. The dual growth exercise suggests that the dual measures of MFP growth for South Korea are very similar to those obtained from the standard growth accounting. Though the real wage experiences a rapid growth at the rate of 4.38%, the resulting MFP growth is moderate due to a sharp decline in the real user cost which ranges between 3.41% - 4.91% for various measures of the real user cost. This is suggestive of consistency between the observed factor prices and the national accounts data set. The reported dual measures for Hong Kong are also very similar to the primal ones. The dual measures for Taiwan exceed the primal ones by at least one percentage point. The author finds the divergence between the two measures of MFP growth to emerge from inconsistencies between the observed real wage growth and the implied real wage growth by the national accounts. Ideally, in the presence of a constant labor income share, real wage and labor productivity should grow at the same rate. However, the real wage growth rate exceeds the labor productivity rate by 1.3 percentage point which causes the dual measures to be inflated. Hsieh argues the output growth from the national accounts to be underestimated as the real wage growth derived from an alternative data source also fails to bridge the gap. As the national accounts of Singapore suggest a sharp rise in the capital to output ratio, the standard measures of MFP growth for Singapore experience negative growth rates. However, the observed real user cost fails to display a similar decline, hence the resulting dual measure of MFP growth substantially differs from the primal ones and grow at least at the rate of 1.5% for alternative measures. This provides evidence of MFP growth contributing significantly to the remarkable growth experience of Singapore. The author argues that the divergence between the two measures originates from inconsistencies between the observed real user cost and the capital stock measures from the national accounts of Singapore and cautions against the reliability of the national accounts data for Singapore. Hsieh (2002) concludes the paper by advocating the utility of the dual accounting framework in the presence of widespread measurement errors in the national accounts data.

Aiyar and Dalgaard (2005) extend the dual growth accounting framework to a development accounting framework to construct the measures of MFP levels for 22 OECD countries. In a variance decomposition approach, the authors find the variations in MFP levels to account for substantial cross country variations in the labor productivity in case of both the primal and dual measures. However, the dual measures diverge considerably from the primal ones and the correlation coefficient is merely 0.46 between the two. As argued earlier, if the data on factor prices and the data on the factor inputs from the national accounts are consistent, the primal and dual measures would yield similar results. Aiyar and Dalgaard (2005) find the source of divergence between the two series to be the inconsistencies between the observed real user cost and the implied real user cost by the national accounts. The authors find the correlation coefficient between the two series to be -0.14. Though the authors do not express any preference over any methodology, they warn for serious data discrepancies for the constructed real user cost and the physical capital stock in the presence of such large inconsistencies between the two series.

It can be clearly inferred from the above discussion that there is a strong utility of the dual growth accounting in the presence of measurement errors in the national accounts data. As Hsieh (2002) argues, the dual accounting method has an added advantage as it relies on observable real factor price data. Hence, the dual growth accounting strongly complements and acts as a tool to corroborate the findings from standard growth accounting exercise.

2.4 Productivity Growth for US Economy

The previous section documented the importance of multi-factor productivity (MFP) growth in explaining the output per worker growth from cross country evidence. In recent times, MFP growth for the US has been a subject of voluminous research in explaining the productivity slowdown of 1973-95. Particularly, sectoral growth performance has been the subject of great attention. While manufacturing industries experienced higher MFP growth, the service sector was the worst affected during this period of productivity slowdown. In a similar fashion, the post 1995 growth revival has also drawn substantial attention in the literature. This section briefly reviews the productivity pattern for the aggregate economy and the major sectors for the US from the available literature.

In Gordon (2000)'s words, MFP growth performance of the US is characterized as "one big wave" where during 1870-1890 MFP growth was slow, after that it accelerated and the peak was achieved during 1913-1972 and post 1972, the famous "productivity slowdown" continued till 1995. Gordon (2000) takes a rather different approach in addressing the slow productivity growth of the late nineteenth century and 1973-1995, and examines the productivity boom of 1913-1973 in stead. Using the standard inputs data on labor and capital, the author finds the MFP growth to display a wave-like pattern where the MFP grows at the rate of 0.77% for 1870-1913, 1.60% for 1913-1972 and 0.62% for 1973-1996. Gordon (2000) attributes this "big wave" pattern to an one-time sharp jump in the output-capital ratio during 1920-1950 especially resulting from an increase in the output to structures ratio. Since MFP growth can be constructed as a weighted average of the growth rates of labor productivity and productivity of capital, an extraordinary growth rate is plausible in the presence of a higher growth rate of productivity of capital. The author addresses the measurement issues related to factor inputs to further analyze the pattern displayed by MFP growth. The literature addressing the productivity issues of the US adjusts the factor input growth for changes in "composition" or "quality" as a part of the MFP growth results from the quality improvements in the factor inputs. The growth rate of labor force is adjusted for changing educational attainments, experience and gender by weighting different groups by their income share. Similarly, the physical capital stock is adjusted for different capital goods using the rental price of capital. The paper contributes to the literature by extending the Bureau of Labor Services (BLS) data set with a comparable data set on the adjusted factor inputs.[3] Gordon (2000) argues the compositional adjustment to reduce the growth rate of output-capital ratio as it puts a higher weight on the "equipments" compared to the "structures" given the relatively higher rental price for "equipments" resulting from higher depreciation rates.[4] Further, the paper adjusts the capital stock data by allowing the retirement pattern to vary for the capital input, and by adding the omitted government owned private operated capital and the government owned infrastructure those being used as inputs in the private production process. The applied adjustment to the capital stock completely eliminates the sharp jump in the output to capital ratio during 1928-1950, hence has strong implications for the pattern of MFP growth. Though the resulting measure of MFP growth still exhibits a wave like pattern, it is much flatter compared to the earlier

[3]The BLS produced data set on adjusted factor input growth and MFP growth is only available from 1948.

[4]The increase in the output to capital ratio features permanently for the "structures" as opposed to the "equipments". Hence, weighting the "equipments" with a higher weight will reduce the growth rate of output to capital growth rate, hence the growth rate for MFP.

estimates and displays growth rates of 0.53%, 0.99% and 0.07% respectively for the period 1870-1913, 1913-1972 and 1972-1996.[5] Further, the author attributes this wave like pattern to four great inventions, namely: electricity, internal combustion engine, processes to create petrochemicals, plastics and pharmaceutical and entertainment, communication and information innovations before the World War II.

In a contribution to the US productivity literature, Triplett and Bosworth (2001) address the productivity growth at the industry level and substantiate the contribution of the service sector to the US productivity slowdown. Utilizing the official BLS estimates of MFP growth, the authors infer that while the non-farm business sector experiences a fall of 1.7 percentage points in the MFP growth, the manufacturing industry experiences only a 0.6 percentage point decline in its productivity growth during 1973-1996 compared to that of 1949-1973. This implies that the service sector has a major role in driving the US productivity slowdown. Additionally, the authors construct the measures of labor productivity growth and MFP growth at the industry level using the data from BEA for 1960-1997. The labor productivity growth for the manufacturing industry slows down by a marginal 0.6 percentage points from 3.3% for 1960-1973 to 2.7% for 1973-1997. On the contrary, the entire service sector experiences a 1.8 percentage points decline in the labor productivity growth. The authors draw similar conclusions for the MFP growth as well.

In recent times, the increasing productivity growth of the information technology (IT) producing industries have received substantial attention in the literature related to the US economy. The declining prices of IT equipments resulting from this continuous productivity growth has led to a significant accumulation of IT capital and contributed significantly in reviving the productivity of the US economy. The paper by Jorgenson et.al. (2005) examines the industry level data for 1977-2000 to trace the sources of economic growth in the US and assess the contribution of IT producing industries. The empirical exercise finds the value added of the US to grow at the rate of 3.08% for 1977-2000. While the contribution of capital input to the growth rate of the US is dominated by non-IT capital with a contribution of 1.09

[5] In a much detailed break up, Gordon (2000) find the MFP to display pronounced growth for the period 1891-1972 compared to the earlier and the later periods.

percentage points, IT capital inputs make an addition of 0.65 percentage points. Similarly, labor input accounts for 1.19 percentage point of this growth with the college educated workforce dominating with a significant 0.72 percentage points contribution. MFP growth accounts for a dismal 0.14 percentage point of the economic growth of US. This dampened growth rate of MFP originates from the non-IT industries. For 1977-2000, while the IT industries experience a MFP growth rate of 0.27%, the non-IT industries depict a growth rate of -0.11%. Further analysis suggests that the growth rate of the value added increases by 1.85 percentage point between 1990-1995 and 1995-2000 displaying evidence of a growth resurgence. Capital input accounts for the majority of this increment with a contribution of 1.02 percentage points with the IT investments dominating with 0.57 percentage points. The IT investments almost double between 1990-1995 and 1995-2000 which results from a further decline in the prices of IT equipments and softwares. Similarly, the contribution of the college educated workforce dominates the contribution of labor input to this growth revival. MFP growth displays an increment from 0.23% to 0.63% between 1990-1995 and 1995-2000, hence adds 0.40 percentage points to the growth acceleration. One of the interesting findings of the study is the gradual increment of MFP growth of the IT industries which dominate the aggregate MFP growth. However, the MFP growth of the non-IT industries displays acceleration only after 1995. The authors conclude the IT investments and higher education to be the major driving forces behind the economic growth of the US. Though MFP growth plays an important role, it contributes less significantly in comparison to the other two factors.

The existing literature attributes the productivity resurgence to IT capital deepening and improvements in the MFP growth in IT producing industries (Jorgenson et.al., 2005). Triplett and Bosworth (2002) address this claim for the IT intensive service sector which was the worst affected during the productivity slowdown. Utilizing the data on twenty seven two digit service industries, the authors evaluate the contributions of MFP growth and capital deepening to the labor productivity growth. The empirical exercise finds the average labor productivity growth for the service sector to be approximately 2.5% post 1995 which is equivalent to the economy wide growth rate of 2.6%. The comparison with the previous time periods is suggestive of huge acceleration in the labor productivity growth which is consistent with the economy wide productivity recovery. Triplett and Bosworth (2002) further extend their analysis to identify the sources productivity resurgence in the service sector. The growth accounting exercise signifies the MFP growth to be the major contributor to the acceleration in labor productivity growth and accounts for more than half of this acceleration. However, the authors argue that IT capital deepening does not play a larger role as compared to MFP growth in the post 1995 resurgence of the service sector, rather they assert that the prominence of IT capital deepening was evident prior to 1995. As opposed to the earlier claims related to IT capital deepening, the paper by Triplett and Bosworth (2002) attribute the success of service sector to MFP growth.

The debate related to the relative importance of IT and MFP growth can be summarized by discussing the paper by Jorgenson et.al. (2008). The growth accounting exercise by the authors suggests a growth rate of 1.49% for labor productivity of the US private economy during the slowdown period of 1973-1995. Capital deepening and MFP growth contribute by 0.85 and 0.39 percentage points respectively. IT capital deepening and IT MFP growth account for 43% of the labor productivity growth. The period of 1995-2000 clearly shows signs of recovery as labor productivity growth improves by 1.22 percentage points and grows at a rate of 2.70%. IT capital deepening and MFP growth in the IT industries account for 78% of this acceleration and clearly contribute significantly to the productivity revival. However, the period of 2000-2005 depicts a completely different story. In comparison to 1973-1995, the labor productivity accelerates by 1.60 percentage points during 2000-2005. While IT capital deepening and IT MFP growth only accounts for 24% of this acceleration, the rest of this acceleration is attributed to non-IT capital deepening, non-IT MFP growth and changes in labor quality. In fact MFP growth accounts for almost half of this acceleration with IT and non IT MFP growth contributing 0.16 and 0.62 percentage points respectively. It can be concluded that IT contributes immensely in reviving the productivity post 1995, however post 2000, its contribution to the productivity growth has been modest and non-IT capital deepening and MFP growth play a significant role in driving the labor productivity growth.

2.5 Literature Related to US States

Due to the absence of state wide data on the capital stock, there is limited research examining the contribution of MFP growth to labor productivity growth for the US states. The existing literature on the regional studies relies on apportioning the industry specific Bureau of Economic Analysis (BEA) capital stock data to the states based on the income share of each state in total income. At the same time, some of the existing literature also assumes the MFP growth to be similar across the states while conducting the state level studies. This section briefly reviews the available literature at the regional level for the US.

The neoclassical growth models suggest that a country tends to grow faster, farther it is away from its steady state level of income. Barro and Sala-i-Martin (1991, 1992) extend this hypothesis to the 48 contiguous US states. The authors argue that since the US states are homogenous in preferences and technology, they will experience similar steady state values. In this case, the poorer states will experience faster growth rates providing evidence for convergence. In the neoclassical set up, the speed of adjustment or the convergence rate varies inversely with the value of capital income share, i.e. the rate at which the diminishing returns to capital operates. Hence, Barro and Sala-i-Martin (1992) argue the rate of convergence to be slower in the presence of a higher capital income share reflecting a slower rate of diminishing returns to capital. An assumption of physical capital income share of 0.35 predicts a speed of adjustment of 12.5% in the quantitative assessment of the authors. On the contrary, a higher value for capital income share (0.8) in order to include human capital results in an adjustment rate of 2.6% annually. The authors argue the theory of convergence using the data sets on per capita personal income and per capita gross state product (GSP) for the US states. The per capita income data set used by the authors is available at intervals prior to 1929 and available annually from 1929 onwards. The used data set on GSP per capita refers to the period 1963-1986. The non-linear least square estimation suggests the rate of convergence to be 1.75% for per capita personal income for 1880-1988. This slower rate of convergence is indicative of diminishing returns to capital to operate slowly. Dividing the time period to nine sub-periods yields the rates of convergence varying between the lowest value of -1.22% to the highest value of 3.73%. The authors reject the null hypothesis of equality of convergence rates across the sub-periods. It is argued that the instability of convergence rates across the sub-periods roots from disturbances affecting specific sectors in different sub-periods. To control for this, the authors introduce a variable reflecting the sectoral composition of the states in the regression. The introduction of this variable yields stable coefficients for the rate of convergence across the time periods and the authors fail to reject the joint hypothesis of equality of the coefficients across the time periods. The restricted estimation yields a coefficient of 2.49% for all the nine sub-periods. This further strengthens the evidence of slower convergence between the states implying slower diminishing returns to capital. The results from the GSP per capita is also very similar to the evidence reported above. After controlling for the sectoral composition, the coefficients for the rate of convergence display less fluctuations across the sub-periods. Again the authors fail to reject the joint hypothesis of equality of the coefficients across the sub-periods and the restricted regression reports a convergence coefficient of 2.16% which is very similar to the reported 2.49% from the per capita personal income. Barro and Sala-i-Martin (1991) in a similar exercise document the evidence of convergence in labor productivity across the states for eight non-agricultural sectors. The authors report higher coefficients for the rate of convergence for the mining, construction, manufacturing and transportation sectors with the manufacturing sector experiencing a very high rate of convergence at 4.6%. The reported rates of convergence for the four service oriented sectors, wholesale and retail trade, FIRE, services and government are very similar and smaller. The authors reject the null hypothesis of equality of convergence rates across the sectors due to a very high value for the manufacturing sector. However, the authors fail to reject the null after dropping the manufacturing sector. The authors further conclude that the convergence across states in per capita personal income and GSP per capita results from the convergence in the labor productivity at the sectoral levels.

Holtz-Eakin (1993) extends the neoclassical growth framework to test the variation in labor productivity across the states and measures the rate of convergence across states. While Barro and Sala-i-Martin (1991, 1992) assume the states to have similar steady state levels, Holtz-Eakin (1993) explicitly control for the steady state determinants. While explaining the variation in labor productivity across states, the author accommodates human capital in the model following the augmented Solow framework of MRW. Apart from data on the state specific labor productivity and population growth rate, one needs the measures of investment rate, human capital to empirically test the augmented Solow framework. Holtz-Eakin (1993) makes use of the data on real investment estimated from the private capital stock estimates by Munnell (1991) and GSP to construct the investment rates. In the first known attempt, Munnell (1991) develops state-specific estimates of private capital stock by apportioning the BEA capital stock data to states. The share of college graduates in the population above 25 years is used as the measure of human capital and is derived from the Census of Population of 1980. Since all the variables except human capital are constructed on an annual basis, the author develops a panel data set to test the Solow framework. The empirical evidence from the steady state equation suggests that the labor productivity shows a positive association with the investment rate. The author finds the income share of capital and human capital to be 0.20 and 0.21 respectively which are lower than the reported 0.3 and 0.28 of MRW. Further, the model fails to explain the majority of variations in labor productivity across the states with an adjusted R-squared of 0.15. The author suggests the low explanatory power to be plausible in the presence of year specific shocks affecting the states differently. Additionally, the author argues the model for the steady state to display low explanatory power, if the states are away from their steady state values. So, the author analyzes the transitional dynamics by estimating the model for convergence. The convergence model does an excellent job in explaining the variation in labor productivity growth across states. Holtz-Eakin (1993) further introduces state-specific measures on land, urban areas, minerals to account for the productivity differences resulting from the differences in state specific endowments. The model reports an implied convergence rate of 4% based on the parameter estimates of the model which is approximately twice those as reported by Barro and Sala-i-Martin (1991, 1992).

The paper by Garofalo and Yamarik (2002) attempts to bridge the gap between the absolute convergence of Barro and Sala-i-Martin (1991, 1992) and the conditional convergence of

MRW. However, in the absence of the state specific measures of capital stock and investment, the application of conditional convergence to the US states is not possible. Garofalo and Yamarik (2002) overcome this obstacle by constructing a data set on the state-wise capital stock by apportioning the national capital stock to the states based on the income shares of the states in total income for each of the nine major industries. This procedure relies on the assumption of equality in the capital to output ratio across the states for an industry. Though perviously an attempt was made by Munnell (1991) to construct the state specific measures of capital stock for each census year, the attempt by Garofalo and Yamarik (2002) clearly improves over the earlier method as it succeeds in creating a yearly time series of the capital stock at the state-level. Secondly, it produces the data set at much finer industry levels and thirdly, it provides a simpler way to update the time series. As discussed earlier, the paper by Holtz-Eakin (1993) also makes an attempt to explore the conditional convergence framework at the state level. However, Garofalo and Yamarik (2002) criticize the earlier attempt as it tries to apply a long-run model to account for the year to year fluctuations in labor productivity in a panel data set up. In their empirical exercise, the authors first examine the production structure of the states utilizing the data set on the physical capital stock and labor. The estimated coefficients of one-third for the capital stock and two-third for the labor force strongly imply the presence of constant returns to scale in the production structure. Augmenting the framework with human capital does not alter the estimate of capital income share of one-third. Further, the authors extend their empirical framework to test for the steady-state equations of labor productivity. The empirical exercise reveals the labor productivity to strongly associate with the investment rates and human capital, but it fails to account for the majority of variations in labor productivity across the states and secondly, the estimated income share for capital fails to match the rule of thumb of one third. So, the authors extend the model to test for the transitional dynamics. The estimated absolute convergence model reports a rate of convergence of 2.1% which is very similar to the reported ones in Barro and Sala-i-Martin (1991, 1992). Further conditioning the model with the steady state income determinants results in rates of convergence between 1.7%-3.1% which is well within the range of the estimates reported by Barro and Sala-i-Martin

(1991, 1992). So, the authors provide evidence for convergence in labor productivity across states in both the absolute and the conditional convergence set up.

The earlier discussed papers assume MFP growth to be similar across the states in a neoclassical framework. The paper by Turner et.al. (2008) assumes MFP growth to vary across states and constructs MFP growth measures to account for its contribution in explaining the variations in labor productivity growth across states in a primal growth accounting exercise. In the primal exercise, MFP growth is backed out as a residual after deducting the factor input growth rates from the labor productivity growth rate. The paper first constructs a data set on the factor inputs for a long period of 1840-2000. While the authors utilize the data on human capital and income from one of their earlier papers (Turner et.al., 2007), the state specific capital stock in the paper is constructed by apportioning the national capital stock to the states based on the income shares of the states as in Garofalo and Yamarik (2002). This methodology relies on the assumption of equalization of capital to output ratio across the states for an industry. The growth accounting exercise reveals that the MFP grows at the rate of 0.56% for the US and accounts 39% of the labor productivity growth which experiences a growth rate of 1.45%. To draw a regional comparison, the authors also report the results for nine census regions. While the MFP growth accounts for a maximum of 44% of the labor productivity growth for New England, for Mountain it only accounts for 33%. Though the factor input growth accounts for a majority portion of productivity growth, the authors further utilize a variance decomposition approach to find out the contribution of MFP growth in explaining the variation in labor productivity growth across the states. Since a unique decomposition of the variance of labor productivity growth is not possible in the presence of the correlation between factor input growth and MFP growth, Klenow and Rodriguez-Claire (1997) allocate one covariance term to MFP growth and the other to factor input growth. Along with this method, the authors also report the contributions of MFP growth by allocating all the covariance to MFP growth and similarly, by allocating all the covariance to factor input growth. This methodology creates an upper-bound and a lower-bound respectively for the MFP growth and similarly, a lower-bound and an upper-bound respectively for the factor input growth in accounting for variations in the labor productivity growth across the states. This alternative methodology reports an upper bound of 93% and a lower bound of 18% for the MFP growth in accounting for the variation in labor productivity growth across states while allocating all the covariance to MFP growth and all the covariance to factor input growth respectively. This wide range originates from a very high correlation between the factor input growth and MFP growth. The authors argue in the presence of institutional homogeneity, one would expect the MFP growth to vary less across the states and account for less of the variations in labor productivity growth. However, the variance decomposition exercise reveals otherwise and the MFP growth still plays an important role accounting for a majority of the variations in labor productivity growth.

The above discussion reveals that the most of the state specific literature assumes MFP growth to be similar and explores the evidence of poor states converging towards the rich states. However, the paper by Turner et.al. (2008) documents the MFP growth to account for a substantial portion of the variations in labor productivity growth across the states. This evidence again reiterates the view of Solow (1957), Denison (1967) and other proponents in highlighting the importance of MFP growth even at the state level.

2.6 Conclusion

This chapter establishes the importance of MFP in explaining the labor productivity and its growth by documenting evidence from the cross-country literature. While the standard growth accounting literature has contributed immensely in substantiating the importance of MFP, in the presence of measurement errors to the physical capital stock, economists have also made use of the dual growth accounting which relies on observed factor prices to further establish the contribution of MFP growth. In a similar fashion, MFP growth for the US has also been a subject of voluminous research in explaining the productivity slowdown of 1973-95 and the subsequent productivity recovery post 1995. Particularly, sectoral growth performance has been the subject of great attention. However, due to the absence of state wise data on the capital stock, there is limited corresponding research examining the contribution of MFP growth to labor productivity growth for the US states which is clearly of importance for state policy making. In fact, the most of the existing literature assumes MFP growth to be similar across states while conducting the state level studies or apportions the industry specific Bureau of Economic Analysis (BEA) capital stock data to the states based on the income share of each state in total income to construct MFP growth measures using the primal growth accounting procedure. However, in the presence of large disparity in labor productivity growth across states, an assumption of equalization of MFP growth across states is clearly unwarranted and secondly, the presence of measurement errors in the physical capital stock calls for the utilization of the alternative dual accounting method to compute the measures of MFP growth.

Chapter 3

Productivity Growth in Manufacturing and Services across US States: What Can We Learn from Factor Prices?

3.1 Introduction

The role of multi-factor productivity (MFP) growth in driving output per worker growth has historically been at the center stage in economic growth research. A large literature examines the role of MFP growth in explaining the disparity in per-capita income growth across countries.[1] A considerable amount of research has also been centered around the importance of MFP growth in explaining the dismal performance of output per worker growth of US during 1973-95.[2] Particularly, sectoral growth performance has been the subject of great attention. While manufacturing industries like computers and office equipments and electronic components experienced higher MFP growth, the service sector was the worst affected during this period of productivity slowdown (Triplett and Bosworth, 2001 and Jorgenson et.al., 2005). Most of this literature uses primal growth accounting to back out MFP growth as a residual from the output per worker growth after taking care of the factor accumulation growth. Due to the absence of state level data on the capital stock, there is a lack of corresponding research examining the performance of state level sector-specific MFP growth within the US. The existing literature on regional studies relies on apportioning the

[1]See Klenow and Rodriguez-Claire (1997), Hall and Jones (1999)

[2]See Gordon (2000), Steindel and Stiroh (2001) and Jorgenson et.al. (2008)

industry-specific Bureau of Economic Analysis (BEA) capital stock data to the states based on the income share of each state in total income (Garofalo and Yamarik, 2002 and Turner et.al., 2008). However, this method of apportioning the national data to the states relies on the assumption of equalization of marginal product of capital across states. This assumption would be affected by compositional differences of industries across states and state tax policies.

In this paper, we employ a dual growth accounting procedure to calculate state-specific MFP growth for the manufacturing and service sectors from 1980 onwards.[3] This approach is based on the fact that any growth to MFP which causes output to grow would also cause real factor prices to grow due to increases in the marginal product of the factors. MFP growth measures can then be constructed as the weighted average of the growth rates of the real factor prices, i.e., the real wage and the real user cost. This approach of measuring the MFP growth using real factor price growth extends at least back to Jorgenson and Griliches (1967).[4] In the process of the dual accounting exercise, our paper makes a unique contribution by constructing a state level data set on the real user cost of capital for the manufacturing and service sectors following the seminal works by Hall and Jorgenson (1967) and Coen (1968).[5] While constructing the real user cost of capital, we pay particular attention to inter-state variations in the composition of output, relative prices of investment goods, state specific effective corporate income taxes, and inflation rates. We construct the state sector-specific investment deflators and depreciation rates by weighting the respective industry-specific national investment deflators and depreciation rates by their state-industrial Gross Domestic Product (GDP) share. The state sector-specific GDP deflators are constructed as the share weighted averages of state industry-specific GDP deflators

[3]We define mining, construction and manufacturing industries together as the manufacturing sector. The service sector includes all the private service providing industries.

[4]See Barro (1999) for a review of this approach. In a more recent application to the East Asian economies, Hsieh (1999,2002) expresses concern over utilizing capital stock data from the national accounts as they are prone to errors due to the computational difficulties. Instead, he advocates the use of the dual growth accounting approach as data on real factor prices is directly observable. Refer Aiyar and Daalgard (2005) for a cross country application and Ciccone and Peri (2006) and Iranzo and Peri (2009) for applications on the US States. However, Ciccone and Peri (2006) and Iranzo and Peri (2009) assume the real wage growth as the measure of dual accounting MFP growth.

[5]Chirinko and Wilson (2008) have constructed a state-wise data set on the real user cost of capital for the manufacturing industry.

where the assigned weights are the industrial GDP shares. The construction of inflation rates follows from the state-sector investment deflators. The state specific effective corporate income tax rate is constructed following Chirinko and Wilson (2008). Using these measures of real user cost and the real wage measures from Integrated Public Use Microdata Series-Current Population Survey (IPUMS-CPS), we construct the state-sector as well as national measures of MFP growth. Some of the key findings of our paper are as follows:

- Though growth in labor productivity is positively associated with MFP growth, variations in MFP growth play a much larger role in the manufacturing sector than in the service sector in explaining the cross-state variations in labor productivity. The contribution of MFP growth in driving labor productivity is higher in the manufacturing sector compared to the service sector.
- The national measures of MFP growth differ substantially from the primal measures derived from the BEA with the service sector registering the maximum divergence. The source of divergence between the two measures originates from inconsistencies between the constructed real user cost and the implied real user cost of the BEA.
- The real user cost of the service sector demonstrates negative growth rate resulting from a rapid decline in the relative price ratio of the investment goods in evidence of "Investment Specific Technological Change (ISTC)" and also implying very high growth in capital accumulation. The implied real user cost of the BEA fails to capture this and registers a positive growth rate instead. The average growth rate of the real user cost for every state is negative due to the ISTC.
- The average growth in the real user cost of capital is non-zero and shows wide variability across states for both the sectors.
- For 1998-2007, the dual measures of the MFP growth are adversely affected by price shocks and business cycle fluctuations.

In our dual accounting exercise, we find the national measure of MFP growth rate to be 2.10% for the US manufacturing sector contributing 68% to Average Labor Productivity

(ALP) growth for 1980-97. This high MFP growth is in line of the existing literature of productivity slowdown which suggests a very high MFP growth for the manufacturing sector (Triplett and Bosworth, 2001 and Jorgenson et.al., 2005). While more than 40 states experience an annual labor productivity growth rate above 2%, around 30 states experience a MFP growth rate above 2%. A strong presence of MFP growth in driving ALP growth can be established by the presence of a strong positive relationship between the two. For the service sector, annual MFP growth is 0.25% contributing only 20% to ALP growth for the US service sector. This is consistent with the finding that the service sector was the worst affected during the productivity slowdown (Triplett and Bosworth, 2001). At the state level, the presence of productivity slowdown is evident given the fact that around half of the states experience ALP growth rates below 1% and around 30 states experience MFP growth rates below the national MFP growth rate of 0.25%. We also conduct a variance decomposition in the spirit of Klenow and Rodriguez-Claire (1997). While the variation in MFP growth explains 39% of the variation in ALP growth across states in the manufacturing sector, it explains only 9% of the variation in ALP growth across states for the services.

When compared to the primal measures of MFP growth derived from the BEA, our national measures of MFP growth differ substantially. The service sector experiences the maximum divergence. We then compare the BEA implied factor price series with our constructed series to pin down the source of divergence. We find that the BEA implied real user cost overestimates the growth rate of the real user cost of capital and hence is the source of divergence between the primal and dual measures of MFP growth. Although, both the BEA implied and our constructed series on the real user cost for US manufacturing register positive growth, our constructed series experience a lower growth due to the marginal fall in the relative price ratio and the fall in the tax component. This positive real user cost growth implies a higher growth rate for MFP which we find for the manufacturing sector. In case of the service sector, where the BEA implied series is characterized by positive growth, our constructed series is characterized by negative growth due to the rapidly falling relative price ratio of the investment goods. There has been a considerable amount of research suggesting the implications for a falling relative price ratio of investment in "equipment and software" due to technological improvements in the "equipment and software" producing industries. Greenwood et.al. (1997) argue that improving technology in the equipment producing industries reduces the relative price of equipment leading to rapid increase in accumulation of equipment and the authors identify this improvement in technology in the equipment producing industries as "Investment Specific Technological Change (ISTC)". The rate of decline in the relative price ratio is identified as the measure of "ISTC" in their model which is 3.21% annually for 1954-90. We find the decline in the ratio to be 2.12% which results in a rapidly falling real user cost of capital, implying higher capital accumulation and lower growth rate for MFP. Given this, the growth rate of our constructed counterfactual real capital stock is 5.11% as opposed to 3.02% of the BEA produced estimates. Our results find support from Greenwood et.al. (1997) who predict a higher growth of equipment accumulation in comparison to the BEA produced estimates.

For the states, we get a positive relationship between the ALP growth and the real user cost growth indicating a stronger presence of MFP growth in driving ALP growth for the manufacturing sector. However, if ALP growth is mostly driven by capital accumulation, one would expect states with very high ALP growth to experience rapid fall in the real user cost of capital for higher growth in capital accumulation. We find evidence of this through a strong negative relationship between the ALP growth and the real user cost growth at the state level for the service sector. The presence of "ISTC" is evident as all the states experience negative real user cost growth due to the rapidly falling relative price ratio of the investment goods. We also find a presence of wide variability of real user cost growth across the states for both sectors.

We use the IPUMS-CPS data to calculate the real wage growth measures at the state level. Use of this micro data set allows us to construct a "quality adjusted" real wage growth based on the educational categories and sex. To rule out the quality adjusted measure of real wage growth as the source of divergence between the primal and dual measures, we carry out the dual accounting exercise using the data on "compensation per full time worker" from the BEA as our measure of real wage. Although the resulting MFP growth improves marginally, it falls far behind the primal measures especially in case of the service sector. This confirms our finding that the inconsistencies between the observed real user cost and the implied real user cost of the BEA create the wedge between the primal and dual accounting measures.

We also carry out the dual accounting exercise for 1998-2007 in North American Industry Classification System (NAICS) data set. We find this short run to be affected by the 2001 recession and the price shocks post 2002 yielding us biased measures of real factor price growth and hence the source of divergence between the primal and dual measures of MFP growth.

The rest of the paper is structured as follows: section 2 establishes the empirical framework required to conduct the dual accounting exercise. Section 3 addresses the data issues. Section 4 discusses the results on the growth performance of MFP, real user cost of capital and the real wage across the states and section 5 concludes.

3.2 Empirical Framework

We briefly explain below the approach put forth by Hsieh (1999, 2002) as it has an advantage in establishing the equality between the quantity and price based measures of MFP growth. This procedure relies on the condition that the income generated in the economy is disbursed between the factors of production, i.e., labor and capital. Given this, the income identity can be portrayed as

$$Y = wL + rK \tag{3.1}$$

where Y = real GDP, L = labor, K = real capital stock, $w = W/P^Y$ =real wage and $r = R/P^Y$ =real user cost of capital and P^Y is the price index used to deflate the GDP. The above identity relies on the assumptions of constant returns to scale and perfect competition given the profits are zero and factor shares add up to one. Under these conditions, factors are paid their marginal product. However, Hsieh (1999, 2002) argues that one does not need any assumptions other than the equality shown in equation (3.1). In presence of profit, the capital share measure will be biased as the equality does not hold any more. Using this biased measure of capital share will affect both the primal and dual MFP growth series and will create a wedge between them. Our empirical exercise focuses on the two major sectors: manufacturing and services at the state level in US. Since goods are tradable across states, the assumption of perfect competition is appropriate. However, the presence of non-tradable goods does exist and this increases the degree of concentration of the industries at the state level. To decrease this degree of concentration and make the assumption of perfect competition more applicable, our definition of the manufacturing sector includes the mining, construction and manufacturing industries together. The service sector which comprises of all the service providing industries (private) is itself large enough at the state level which implies a lower degree of concentration and hence makes the assumption of perfect competition reasonable.

The idea behind dual accounting is that any growth to MFP that would increase output, would also raise the return to the factors of production. In that case, MFP growth can be measured as a share weighted average of growth rates of returns to the factors of production, i.e., real wage and real user cost growth rates. An equivalence between primal and dual accounting can be obtained by time differentiating the equation (3.1) and dividing it by Y,

$$\dot{Y} = \dot{w}L + w\dot{L} + \dot{r}K + r\dot{K} \tag{3.2}$$

$$\frac{\dot{Y}}{Y} = \frac{\dot{w}}{w}\frac{wL}{Y} + \frac{\dot{L}}{L}\frac{wL}{Y} + \frac{\dot{r}}{r}\frac{rK}{Y} + \frac{\dot{K}}{K}\frac{rK}{Y} \tag{3.3}$$

$$\hat{Y} = \alpha_L(\hat{w} + \hat{L}) + \alpha_K(\hat{r} + \hat{K}) \tag{3.4}$$

$$\hat{Y} - \alpha_K\hat{K} - \alpha_L\hat{L} = \alpha_K\hat{r} + \alpha_L\hat{w} \tag{3.5}$$

Here α_L is the labor income share and α_K is the capital income share which is equal to $(1-\alpha_L)$. The "ˆ" sign on the variables denotes the growth rates of the variables. In the last equation, the expression on the left represents the MFP growth measures from the primal (quantity) growth accounting and the expression on the right represent the dual accounting measures. Primal growth accounting measures derived from the Bureau of Economic Analysis (BEA) data will coincide with the dual measures if the observed factor prices are consistent with the implied factor prices of national accounts of the BEA. Any differences between them would create a wedge between the two measures (Hsieh, 1999, 2002 and Aiyar and Daalgard, 2005). However, Hsieh (1999, 2002) and Aiyar and Daalgard (2005) find divergence in these two measures as evidence of inconsistencies between the observed factor prices and the implied factor prices of national accounts.

To obtain the measures of MFP growth, we need to construct the measures of labor income share, real user cost growth and real wage growth for the sectors at the state level. In the following sub-sections, we outline the computational details of these measures.

3.2.1 Labor Income Share

It is evident from equation (3.5) that the income share of labor plays an integral part in constructing the MFP growth rate. Conventionally, the state level labor income share has been assumed to be equal to its national counterpart. For example, Turner et.al. (2008) approximates the state aggregate labor income share to be equal to the national counter part of 0.667. This practice is inappropriate for our exercise as we focus on the two major sectors at the state level and different sectors at the state-level are likely to operate at different technologies leading to varying labor income shares. A recent study by Valentinyi and Herrendorf (2008) cautions against applying the US aggregate factor income share to the sectors. They find that the factor income shares for five major sectors (Agriculture, Manufacturing Consumption, Services, Equipment Investment and Construction Investment) of US vary significantly. Moreover, industry composition varies across states. Therefore, even if the industry level labor share is same across states, the sectoral labor income share across states will still vary because of the varying industry mix. In this scenario, approximating sector level labor share of the state by its national counter-part would lead to misleading estimate of MFP growth. With this background, following Gollin (2002) and Gomme and Rupert (2004), we compute the sector and state specific labor income share as

$$\alpha_{L,i,s,t} = \frac{\dfrac{Compensation\ of\ Employee_{i,s,t}}{Wage\ and\ Salary\ Employment_{i,s,t}} \times Total\ Employment_{i,s,t}}{SGDP_{i,s,t} - ITS_{i,s,t}} \tag{3.6}$$

where $\alpha_{L,i,s,t}$ is the labor income share of sector "i" and state "s", "ITS" is the taxes on production and imports less subsidies and "SGDP" is the state gross domestic product. This method of computing labor income share takes care of the self employed by imputing them a compensation equal to the average compensation of wage and salary employed (Gollin, 2002).

3.2.2 Real User Cost of Capital

The foundations of the framework of the real user cost of capital is established by the seminal works by Hall and Jorgenson (1967) and Coen (1968).[6] In this framework, a profit maximizing competitive firm invests in capital till the marginal product of capital is exactly equal to the real user cost of capital. Following these papers, the real user cost for sector "i" and state "s" can be defined as[7]

$$RUC_{i,s,t} = \frac{P^I_{i,s,t}}{P^Y_{i,s,t}}(i_t + \delta_{i,s,t} - \pi_{i,s,t})\frac{(1-\tau_{s,t}z_{i,s,t})}{(1-\tau_{s,t})} \tag{3.7}$$

Here, a decision to invest in one unit of capital depends on $\frac{P^I_{i,s,t}}{P^Y_{i,s,t}}$ which represents the relative price of the new capital good in terms of the price of the final good, the real interest rate which is the financial cost of this investment $(i_t - \pi_{i,s,t})$, the depreciation rate of the capital goods $(\delta_{i,s,t})$ and the tax applications in terms of the effective corporate income tax $(\tau_{s,t})$ and the present value of depreciation deductions $(z_{i,s,t})$. Here $\frac{(1-\tau_{s,t}z_{i,s,t})}{(1-\tau_{s,t})}$ of the real user cost can be viewed as a tax subsidy. If the government does not provide any tax benefits in terms of depreciation deductions i.e. $z_{i,s,t} = 0$, the real user cost will increase by a fraction $\frac{1}{(1-\tau_{s,t})}$.

We construct the $P^I_{i,s,t}$ as a share weighted implicit price deflator using the US sub-sectoral (industrial) investment price deflators. $P^Y_{i,s,t}$ is constructed by weighting the state-

[6]While Hall and Jorgenson (1967) in a continuous time model allow for investment tax credit, the model by Coen (1968) does not take it into account. We have omitted investment tax credit while constructing the real user cost as the federal investment tax credit was rolled back in 1986 and although some states allow for investment tax credit, most of the time it is industry specific.

[7]For convenience, we index the state with subscript "s", the major sectors (manufacturing and services) with subscript "i" and the sub-sectors (industries) with subscript "j".

specific SGDP deflators of the sub-sectors. $\delta_{i,s,t}$ is a share-weighted real depreciation rate of the national sub-sectoral real depreciation rates. The assigned weights are the SGDP share of each industry (sub-sector) in total sectoral SGDP of the state. i_t is the nominal interest rate, $\tau_{s,t}$ is the state specific effective corporate income tax rate which is constructed following Chirinko and Wilson (2008), $z_{i,s,t}$ is the present value of depreciation deductions of \$ 1 investment which is calculated using the double declining balance method by Hall and Jorgenson (1967) using state sector-specific depreciation rate $\delta_{i,s,t}$. Following Gilchrist and Zakrajšek (2007), the inflation rate $\pi_{i,s,t}$ is constructed as a five year moving average of lagged inflation of investment prices indices $P^I_{i,s,t}$. Henceforth, we refer to $\frac{P^I_{i,s,t}}{P^Y_{i,s,t}}$ as the relative price ratio, $(i_t + \delta_{i,s,t} - \pi_{i,s,t})$ as the financial component and $\frac{(1-\tau_{s,t} z_{i,s,t})}{(1-\tau_{s,t})}$ as the tax component of the real user cost.

The base year for the price indices used in our analysis is 2000 which implies that the relative price ratio is 1 for the year 2000. However, in reality there is no need for the relative price ratio to be 1. If it is true, the constructed real user cost series will be measured with error for the base year. This error in relative price ratio in one year will be carried forward to other years as well though this will not matter for the growth rate of the series, hence our constructed real user cost series need to be adjusted for every year. Ideally, our constructed user cost should match the BEA implied real user cost of capital. Given this, we apply a level adjustment to our series on real user cost ($RUC_{i,s,t}$) based on the ratio of the BEA implied real user cost of capital and the weighted real user cost for sector "i" for US for 1980 which is the starting year of the Standard Industrial Classification (SIC) data set.[8] We construct the BEA implied real user cost as

$$RUC\_BEA_{i,t} = \frac{(1-\alpha_{L,i,US,t})Y_{i,US,t}}{K_{i,US,t}} \tag{3.8}$$

and our adjustment procedure for sector i can be expressed as

[8]The error carried forwarded to the other years due to the base year problem is same for every year. In that case, correcting the series based on one year's ratio corrects the error for the whole series. For North American Industrial classification System (NAICS) dataset, the correction is applied for 1998.

$$\frac{RUC\_BEA_{i,1980}}{WT.RUC_{i,1980}} = \frac{Adj\_RUC_{i,s,t}}{RUC_{i,s,t}} \tag{3.9}$$

"$WT.RUC_{i,1980}$" is a share weighted real user cost constructed by applying capital income share of each state in total capital income to the state specific real user cost for any sector "i". Our real user cost series for the rest of the analysis is "$Adj\_RUC_{i,s,t}$". Since the applied adjustment is based only on 1980's value, the growth rate of the adjusted series will not be different from the original series. For any state "s" and sector "i", the growth rate of the real user cost between two years is calculated as the log difference of the constructed real user cost.[9]

3.2.3 Real Wage Growth Rate

Our constructed series on real wage growth is quality-adjusted based on different kind of labor groups. Following Hsieh (2002), the labor groups are based on four educational categories (some school, high school graduate, some college and college graduates) and gender. With this, we have eight groups of labor in each sector and state. This quality adjustment ensures that real wage growth only results from the real wage growth of a labor group and not due to the increase in the share of that labor group which increases the average real wage. Allowing for different groups, the weighted real wage growth rate of the sector "i" and state "s" is

$$\hat{w}_{i,s,t} = \sum_j \bar{S}_{L,j,i,s} \hat{w}_{j,i,s,t} \tag{3.10}$$

Here $\bar{S}_{L,j,i,s} = \frac{S_{L,j,i,s,t}+S_{L,j,i,s,t-1}}{2}$ and $S_{L,j,i,s,t}$ is the share of labor income of each group in total labor income and $j = education \times gender$. Total income of each group and sector can be obtained by summing over the labor income of all the individuals. The nominal wage is deflated using the implicit price deflator of SGDP for sector "i".

[9]The measure of the real user cost growth is not adjusted for quality based on different kind of capital goods due to the lack of data at the state level.

3.2.4 Multi-Factor Productivity Growth Rate

In dual accounting framework, MFP growth rate can be measured as a share weighted average of the growth rates of the returns to the factors of production i.e. real wage and real user cost growth rates. So, the measures of MFP growth are constructed by weighting the measures of real wage growth and real user cost growth by the labor income share (α_L) and the capital income share ($1-\alpha_L$) respectively. The MFP growth rate for sector "i" and state "s" can be represented as

$$MFPG_{i,s,t} = \bar{\alpha}_{K,i,s}\hat{r}_{i,s,t} + \bar{\alpha}_{L,i,s}\hat{w}_{i,s,t} \tag{3.11}$$

where $\bar{\alpha}_{L,i,s} = \frac{\alpha_{L,i,s,t}+\alpha_{L,i,s,t-1}}{2}$, $\bar{\alpha}_{K,i,s} = \frac{\alpha_{K,i,s,t}+\alpha_{K,i,s,t-1}}{2}$ and $\hat{r}_{i,s,t} = Adj\_\hat{R}UC_{i,s,t}$.

We also construct the MFP growth series for US using the weighted real wage growth and real user cost growth measures of US derived from the state level measures. For a sector "i", the real user cost growth rate for US is constructed as a share weighted average of the growth rates of the state specific real user cost where the assigned weights are the capital income share of each state in total capital income of US. Similarly, the national measures of real wage growth are constructed by applying the labor income share of each state in total national labor income to the state specific measures of real wage growth.

3.3 Data Sources

This section briefly documents the data used for our empirical analysis. The data appendix section deals with the definitions and sources in greater detail. The data is in Standard Industrial Classification (SIC) for years 1980-1997 and in North American Industrial Classification System (NAICS) for years 1998-2007. Because of incompatibilities, we present the results separately for both classifications. The nominal series are converted to real series using the price indices with base year 2000.

To construct the factor income share series at the state level, we use the data on State Gross Domestic Product (SGDP), Compensation of Employees, ITS, Wage and Salary Employment and Total Employment published by the BEA Regional Accounts Section. To construct the series on real user cost, we require data on the nominal interest rate, state-sector specific investment price deflators, SGDP deflators, depreciation rates and the state effective corporate income tax rates.[10] The nominal interest rate is a twelve-month average of Moody's Seasoned AAA Corporate Bond Yield available at St. Louis Federal Reserve Bank web site. Our state-sector specific measures of investment deflators and depreciation rates are share weighted measures of US sub-sectoral (industrial) investment deflators and depreciation rates respectively where weights are the SGDP share of industry "j" in sector "i". The investment price deflators for US industries are constructed using the industry-specific "Investment in Private Fixed Assets" and its "Chain-type Quantity Indices" from the BEA Standard Fixed Assets tables. The industry specific measures of real depreciation rate for US are constructed using the industry specific real depreciation cost and real net capital stock of private fixed assets. We use the data from the BEA Standard Fixed Asset tables on "Current Cost Depreciation of Fixed Assets", "Chain-type Quantity Indices" for depreciation to construct real depreciation cost and "Current Cost Net Stock of Private Fixed Assets" and it's "Quantity Indices" to construct real net capital stock of private fixed assets.

The SGDP deflator for sector "i" is constructed by applying SGDP share of industry "j" to SGDP deflator of industry "j". The industry specific SGDP deflators for each state are constructed using the state-industry specific data on SGDP, real SGDP and quantity indices of SGDP from the BEA Regional Economic Accounts. Effective corporate income tax rates for the states are constructed using the data on federal corporate income tax rates from the Tax Foundation and the data on state corporate income tax rates and federal tax deductibility from various editions of the "Book of the States" published by the Council of the State Governments.

To construct a "quality adjusted" measure of real wage growth, we rely on the micro data set of March Current Population Survey (CPS) published at IPUMS-CPS for 1980-2008.

[10]The present value of depreciation deductions and the inflation rates are calculated using the constructed series on the depreciation rates and investment price deflators respectively.

Quality adjustment is applied based on four educational groups of labor (some school, high school graduate, some college and college graduate) and gender. Our measure of annual real wage growth is based on the weekly wages derived from this data set.[11] Our constructed wage growth and weeks worked corresponds only to full time equivalent employees. So, anybody working below 35 hours a week and 40 weeks per year is dropped from the sample.[12] Our constructed series on the state-sector specific Average Labor Productivity (ALP) is output per weeks worked. The series on ALP is constructed using the data on SGDP, total employment and the measure of average weeks of work derived from IPUMS-CPS.

3.4 Results

We discuss the results obtained through dual growth accounting in this section. Because of incompatibilities, we present the results for SIC and NAICS classifications in two separate subsections. We present the state-weighted national measures of MFP growth first and compare them with the available literature for validity.[13] We also contrast our measures with those procured through the primal accounting exercise using the data from the BEA for US. Subsequently, we analyze the components of dual MFP growth measures to pinpoint the sources of divergence between the dual and primal accounting measures. Discussion for the states follows the national discussion.

3.4.1 Standard Industrial Classification (1980-1997)

3.4.1.1 Multi-Factor Productivity (MFP) Growth

US Manufacturing and Services: Table (3.1) displays the results for the manufacturing sector for the period 1980-97. Even though 1980-97 was a period marked by the produc-

[11] Autor et.al. (2008) cautions against using hourly wage distribution in March-CPS data set as it lacks a point-in-time measure. An estimate of total hours worked last year can be obtained by multiplying weeks worked in the last year and usual hours worked per week last year in March-CPS data. But Autor et.al. (2008) find this measure problematic.

[12] We also tried our analysis with different hour and week combinations, but that did not affect our results.

[13] As a robustness check, we also present the direct measures of MFP growth using the real user cost growth and the real wage growth for US. We find that the state weighted measure match very closely to the national measures. We use the state weighted measures as our bench mark results.

Table 3.1: **Average Annual MFP Growth Rate (US-Manufacturing) (1980-1997).** Note: The presented numbers are in percentages. ALPG=Average labor productivity growth rate, RWG=Real wage growth rate, RUCG=Real user cost growth rate, MFPG=Multi-factor productivity growth rate, TB=Primal growth rates reported in Triplett and Bosworth (2001), Primal=Our primal measures of MFP growth rate calculated using the data from the BEA.

	IPUMS-CPS		Compensation			
	St.Wt.	US	St.Wt.	US	TB	Primal
ALPG	3.08	2.99	3.12	3.03	2.03	3.03
RWG	2.13	2.04	2.54	2.47		
RUCG	2.00	1.66	2.00	1.66		
MFPG	2.10	1.92	2.42	2.24	1.44	2.65

tivity slowdown, manufacturing sector experienced higher productivity growth during this period. This can be attributed to the fact that when the productivity slowdown was in force, manufacturing industries like computers and office equipments and electronic components experienced a higher MFP growth than the other industries (Jorgenson et.al., 2005). Triplett and Bosworth (2001) argue that for the period 1973-97, manufacturing industry experienced a MFP growth rate of 2.0% annually and even during the sub-period of 1987-97, all the three industries inside the manufacturing sector: mining, construction and manufacturing experienced rapid increases in MFP growth. According to our calculations, ALP grows at a very high rate of 3.08% annually for the manufacturing sector. The real factor prices i.e. real wage and real user cost also display very high annual growth rates of 2.13% and 2% respectively. The dual measure of MFP growth displays an annual growth rate of 2.10% contributing 68% to the ALP growth. These findings are consistent with the existing literature which provides evidence of a larger contribution of MFP growth in driving ALP growth. Our results find support from Triplett and Bosworth (2001) who report the MFP growth rate to be 1.44% for the manufacturing sector comprising 71% of the ALP growth for 1973-97.[14] Our reported growth rates differ from them as the time period for both the studies does not coincide and secondly, RGDP experiences a higher growth due to a conversion to the chain-weighted price and quantity indices in 1999 by the US national accounts (Gordon, 2006), hence generating a higher growth rate for ALP and MFP. Following Triplett

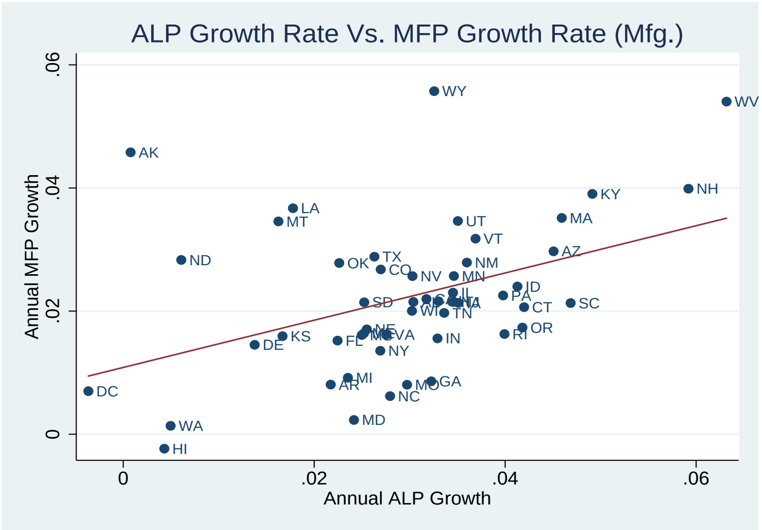
[14]Triplett and Bosworth (2001) report the ALP growth and the primal measures of MFP growth for the major SIC industries for 1973-97 using the capital stock, persons engaged in production data from the BEA.

and Bosworth (2001), we carry out a primal exercise for US manufacturing using the data on the physical capital stock and persons engaged in production from the BEA. The primal exercise yields a MFP growth rate of 2.65% per annum which contributes 87% to the ALP growth which is much higher than the dual measures. This has clear implications for the divergence between the growth rates of the observed factor price and the implied factor prices from the BEA.

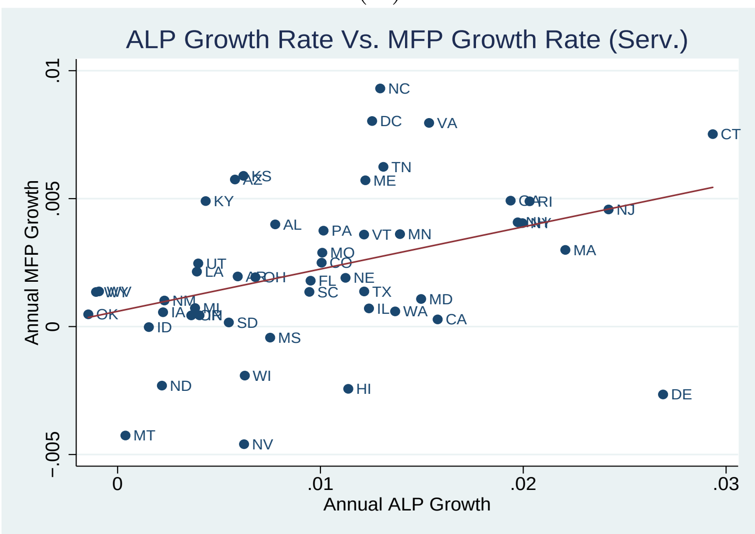
Table 3.2: **Average Annual MFP Growth Rate (US-Services) (1980-1997).** Note: The presented numbers are in percentages. ALPG=Average labor productivity growth rate, RWG=Real wage growth rate, RUCG=Real user cost growth rate, MFPG=Multi-factor productivity growth rate, TB=Primal growth rates reported in Triplett and Bosworth (2001), Primal=Our primal measures of MFP growth rate calculated using the data from the BEA.

	IPUMS-CPS		Compensation			
	St.Wt.	US	St.Wt.	US	TB	Primal
ALPG	1.24	1.24	1.26	1.26	0.4	1.26
RWG	0.96	0.92	1.17	1.12		
RUCG	-0.92	-0.90	-0.92	-0.90		
MFPG	0.25	0.23	0.38	0.36	0.2	1.13

Table (3.2) reports the dual growth accounting measures for the service sector. The ALP grows at a much slower rate of 1.24% when compared to manufacturing. While the real wage grows at the rate of 0.96% annually, the real user cost registers a negative growth rate of -0.92% resulting in a very low annual MFP growth of 0.25%. This low MFP growth contributes only 20% to the ALP growth and implies a greater role for factor accumulation in explaining the ALP growth. Our results of very low growth rates for ALP and MFP garner support from the existing literature which provides evidence that the service sector was the worst affected during the productivity slowdown (Triplett and Bosworth, 2001 and Jorgenson et.al., 2005). Triplett and Bosworth (2001) report the MFP growth rate to be 0.2% which is very close to our produced results. This is due to the fact that they report the results for 1973-97 and during 1973-80, the impact of the slowdown was at its peak leading to a very low MFP growth for the service sector and secondly, the data used by them does not involve the revision applied to the national accounts in 1999 which implies a higher growth for RGDP, hence higher growth rates for ALP and MFP. Our primal measures report a growth rate of 1.13% for MFP which is around 90% of the ALP growth. This finding of primal accounting is contradictory to the productivity slowdown literature. Since the dual measures of MFP growth diverge hugely from the primal measures, it is worthwhile to compare the BEA implied real factor prices and our constructed real factor prices to track the source of this divergence.



(A)



(B)

Figure 3.1: **ALP Growth Vs. MFP Growth (1980-1997)**

State Manufacturing and Services: Figure (3.1) panel (A) displays the average ALP growth rate against the average MFP growth rate for the manufacturing sector for 1980-97. As discussed earlier, during the productivity slowdown manufacturing sector experienced very high growth rates of ALP and MFP. This finding is also evident at the state level. While more than 40 states experience an annual ALP growth rate above 2%, around 30 states experience a MFP growth rate above 2%. A strong presence of MFP growth in driving ALP growth can be established by the presence of a strong positive relationship between the two in figure (3.1) panel (A). While states like West Virginia, New Hampshire, Kentucky, Massachusetts, Arizona are characterized by very high MFP growth rates resulting in very high ALP growth rates, states like Hawaii, Washington, Maryland, Delaware, Kansas, and Arkansas represent the lower end of this relationship. States with a greater share of mining industry like Alaska, North Dakota, Montana, Louisiana and Wyoming are those, experience very high factor price growth resulting in MFP growth rates higher than the ALP growth rates implying negative factor input growths.[15] MFP growth contributes more than 50% to ALP growth for 35 states which is in accordance of the national trend. This contribution is more than 65% for the states with very high ALP growth rates like West Virginia, New Hampshire, Kentucky, Massachusetts, Arizona.

The relationship between the ALP growth and MFP growth for the service sector is displayed in figure (3.1) panel (B). The presence of the productivity slowdown is evident given the fact that around half of the states experience ALP growth rates below 1% and around 30 states experience MFP growth rates below the national MFP growth rate of 0.25%. Although there exists a positive relationship between the two indicating that states with higher ALP growth associate themselves with higher MFP growth, this relationship is weak. States like Connecticut, New Jersey, Massachusetts, New York, Rhode Island displaying very high ALP growth are not the frontier states in MFP growth and for these states, ALP growth is driven by very high accumulation of capital. North Carolina, DC, Virginia, Tennessee, Maine display very high MFP growth even though the ALP growth is not high. The contribution of MFP growth in driving ALP growth is less than 35% for 40 states. For states experiencing very high ALP growth such as Connecticut, Delaware, New Jersey, Massachusetts, Rhode Island, New York, Georgia, the contribution of MFP growth

[15] Triplett and Bosworth (2001) provide evidence for the construction industry which experiences MFP growth higher than the ALP growth for the period of 1973-97 and for the sub-period 1987-97.

to ALP growth is less than 25%.

Variance Decomposition: We conduct a variance decomposition exercise following Klenow and Rodriguez-Clare (1997) to determine the contribution of MFP growth in explaining the variation in ALP growth across states in US. Since ALP growth can be represented as the product of MFP growth and factor input growth (residuals), variations in ALP growth will add up to the variations arising due to MFP growth and residuals.

$$Var(ALPG) = Var(MFPG) + Var(RESID) + 2Cov.(MFPG, RESID) \tag{3.12}$$

$$1 = \frac{Var(ALPG)}{Var(ALPG)} = \frac{Var(MFPG)}{Var(ALPG)} + \frac{Var(RESID)}{Var(ALPG)} + 2\frac{Cov.(MFPG, RESID)}{Var(ALPG)} \tag{3.13}$$

Following Klenow and Rodriguez-Clare (1997), we allocate one covariance term to MFP growth (MFPG) and the other to the residuals (RESID). With this, the implied contribution of MFP growth in explaining the variations in ALP growth across the states can be represented as

$$\frac{Var(MFPG) + Cov.(MFPG, RESID)}{Var(ALPG)} \tag{3.14}$$

Table 3.3: **Variance Decomposition (1980-1997).** Note: N=Number of states included, N=45 drops the top 3 states and the bottom 3 states based on MFPG.

Shares	Manufacturing		Services	
Var(MFPG) share	0.84	0.59	0.16	0.12
Var(RESID) share	1.07	0.98	0.98	0.76
Cov(MFPG, RESID) share	-0.45	-0.28	-0.07	0.06
Implied Share of MFPG	0.39	0.31	0.09	0.18
Implied Share of RESID	0.62	0.7	0.91	0.82
N	51	45	51	45

Table (3.3) presents the variance decomposition exercise carried out for both sectors. For the manufacturing sector, variations in MFP growth explain 39% of the variations in ALP growth across states and the remaining variations result from the variations in the factor input growth. This result can be justified by the fact that manufacturing sector experienced a higher MFP growth and contributed immensely in driving ALP growth during 1980-97.

Hence, variations in MFP growth result in greater variability in ALP growth. After dropping the 3 states with the highest and 3 states with the lowest MFP growth, the contribution of MFP growth declines slightly to 31%. The variations in MFP growth explain only 9% of the variations in ALP growth across the states for the service sector. This result is in accordance with the literature as during the productivity slowdown, dampened MFP growth contributed very less in driving the ALP growth. So, the variations in ALP growth results more from the variations in factor accumulation. After dropping the top 3 and bottom 3 states in MFP growth, the contribution of MFP growth improves to 18% but the importance of factor accumulation is still well acknowledged.

Our discussion on the MFP growth measures suggest that although the dual accounting measures are consistent with the productivity slowdown literature, these measures substantially differ when compared to the primal growth accounting measures at the national level, so we analyze individual components of dual growth measures to pin down the source of divergence in the following sub-sections.

3.4.1.2 Labor Income Share

We use the labor income share derived from the BEA data set for both primal and dual accounting exercise, so this can not be a source of divergence between the two measures. However, labor income share is an important component for measuring MFP growth. So, we briefly discuss our results on labor income share here. US manufacturing and service sectors experience average labor income shares of 0.72 and 0.62 respectively for 1980-97. There has been a growing perception of declining labor income share in US.[16] Our results at the national level are in consensus with this perception.[17] Figure (3.2) panel (A) plots the state-wise labor income share for the manufacturing sector. Since it is difficult to visualize the time series for all the 50 states and DC in one figure, we present the results of the beginning year against the end year to get a perception of the common trend. The manufacturing sector is characterized by very high labor income shares across states. Huge variations in state-wise

[16]The reader can refer to Gomme and Rupert (2004) for a discussion on this.

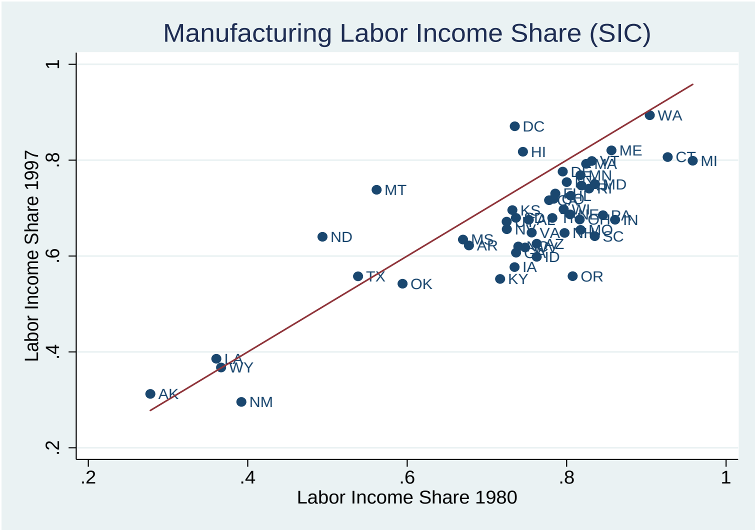
[17]We do not present the time series of labor income share of US manufacturing and service sector in this paper, but our findings do support this perception.

labor share are evident in the figure. It can be inferred from the forty five degree equality line that in 1997 most of the states experience a drop in the labor income share in comparison to the same of 1980 which is in accordance with the growing perception of declining labor income share. The low labor income shares of Alaska, Louisiana, New Mexico and Wyoming can be attributed to the presence of larger natural resource rich mining industry. Figure (3.2) panel (B) portrays the results for the service sector. The labor income share for the most of the states lie within the range of 0.55 to 0.7. DC is a clear outlier with a very high labor income share. One can find the presence of variations in labor income share across states but these variations are not as large as the manufacturing sector. There is a decline in the labor share but it is moderate when compared to the manufacturing sector.

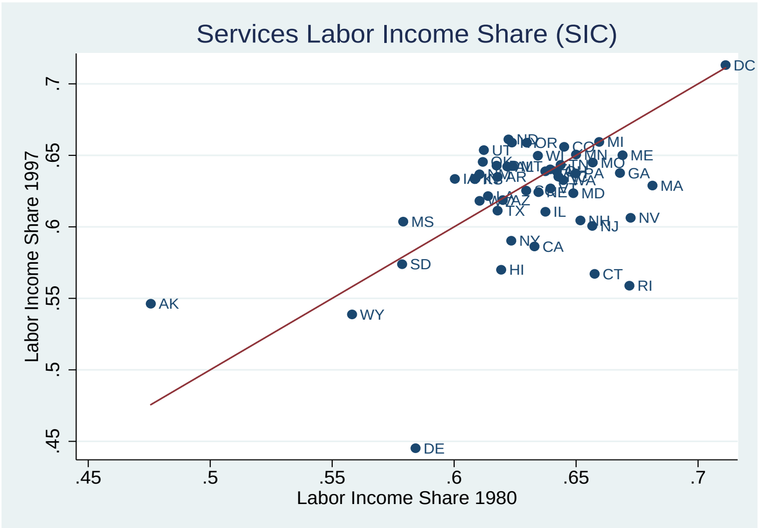
3.4.1.3 Real User Cost of Capital

US Manufacturing and Services: In this section, we compare the BEA implied real user cost with our constructed real user cost to pinpoint the source of divergence between the primal and dual measures of MFP growth. Figure (3.3) panel (A) displays the adjusted weighted real user cost (Adj.Wt.RUC) against the BEA implied real user cost of capital (RUC_BEA) for US manufacturing sector. Since the adjustment is applied for 1980, both series have the same starting point.[18] "Adj.Wt.RUC" closely follows the movement of "RUC_BEA" till 1992, but post 1992, it diverges from "RUC_BEA" and falls below it. While the averages are 0.199 and 0.176 for 1980-92, the averages are 0.207 and 0.231 for 1993-97 for "Adj.Wt.RUC" and "RUC_BEA" respectively. Chirinko and Wilson (2008) find the average real user cost for the manufacturing industry to be 0.248 for a panel of 48 states for the time period 1982-2004. Figure (3.3) panel (B) represents the components of "Adj.Wt.RUC" normalized to their 1980 values. It can be seen from figure (3.3) panel (B) that our financial component closely follows the movement of "RUC_BEA". The increasing trend of our constructed series till 1989 can be attributed to the following: firstly, the in-

[18]It is important to recall that the real user cost of capital for US is constructed by applying weights to the state-level measures where weights are capital income share of each state in the total capital income. The adjusted weighted user cost displayed in the figures is the result of base year adjustment applied to the weighted real user cost as given in equation (9).



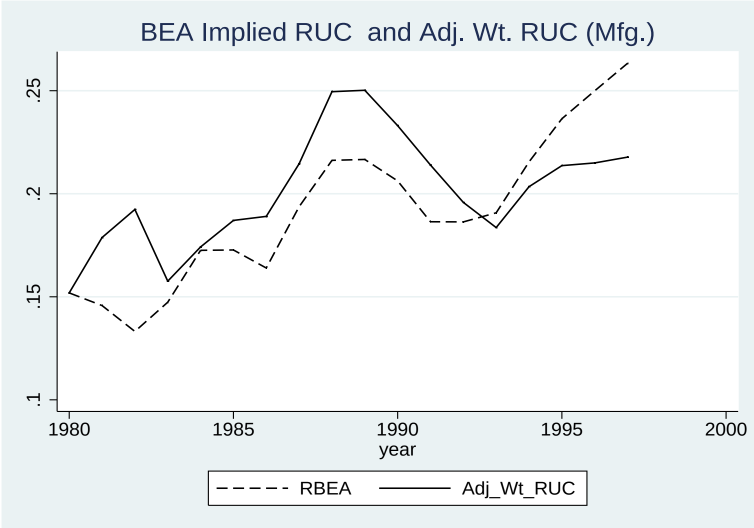
(A)



(B)

Figure 3.2: **Labor Income Share (1980-1997)**

flating financial component due to a very high nominal interest rate to tackle the worsening inflation of 1970's. Between 1980-1989, as a result of this tightened monetary policy the inflation rate falls faster than the interest rate causing the financial component to increase. Secondly, the relative price ratio shows an increasing trend till 1988 due to a higher inflation rate in the investment price deflator compared to the same in the GDP deflator and thirdly, to a very high corporate income tax rate of 46% in US. Post 1989, the nominal interest rate falls down after a period of low inflation rate which suppresses the financial component (moreover, the 1991 recession contributes to the falling interest rate). The relative price ratio shows a marginal decline post 1988, but it is not very substantial. Greenwood et.al.



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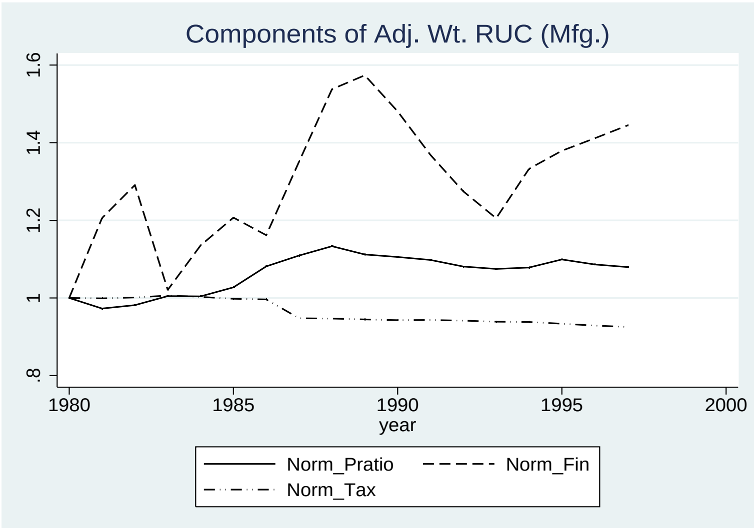


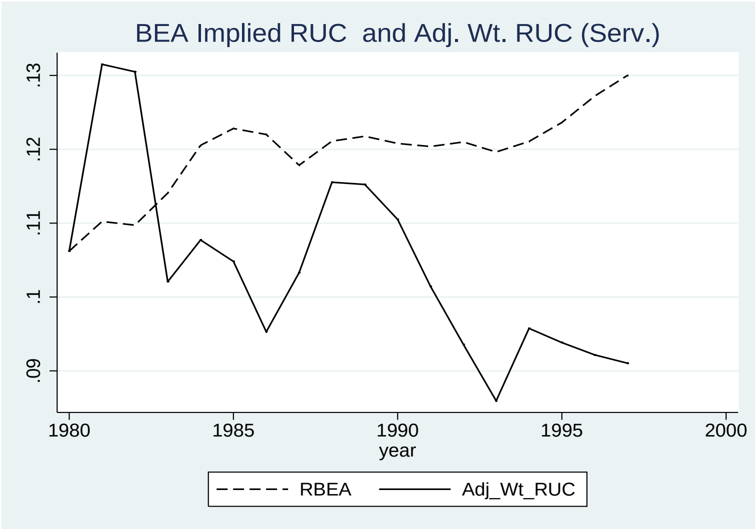
(B)

Figure 3.3: **BEA Implied Real User Cost and Adjusted Weighted Real User Cost (Manufacturing) (1980-97)**

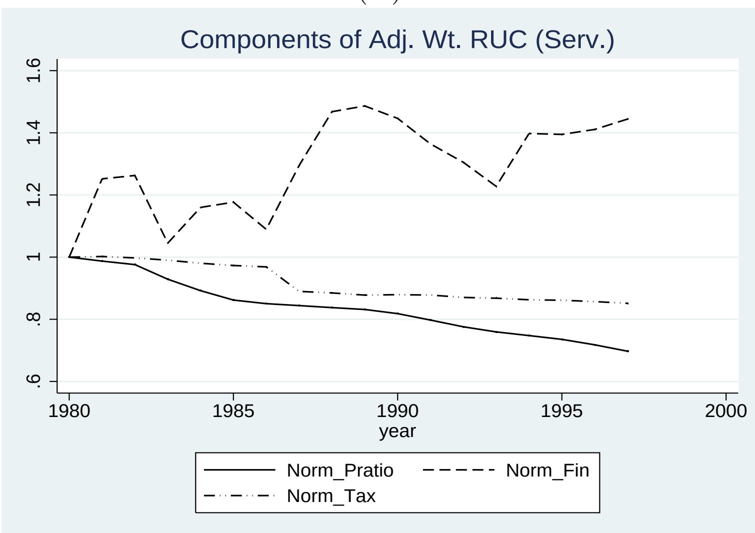
(1997) argue that the relative price ratio for "equipment" is declining over time as a result of increasing productivity in the "equipment and software" producing industries causing an increase in accumulation of "equipment and software". The slight decline in the relative price ratio post 1988 can be assigned to the fact that the investment price deflator used for our paper represents the deflator for both "equipment and software" and "structures". For the period 1977-95, industries inside manufacturing sector do not experience huge growth in non-IT investment (Jorgenson et.al., 2005). Another major factor which contributes in suppressing our real user cost of capital is the huge cut in the federal corporate income tax rate to 34% in 1987. From 1994, the financial component increases slightly but this increase is not high enough to push our constructed series beyond the BEA's. It can be viewed that our constructed series exhibits a lower growth compared to the BEA's which attributes a higher growth rate for the capital stock as compared to the same of the BEA produced capital stock. However, the constructed real user cost registers a positive growth which has implications for a higher MFP growth in explaining the growth of manufacturing sector. Given the lower growth of the constructed real user cost series compared to the implied series of BEA, the dual measures of MFP growth result in lower growth compared to the primal measures.

Figure (3.4) panel (A) plots our constructed "Adj.Wt.RUC" against the "BEA_RUC" and panel (B) displays the movements of its normalized components for the service sector for the period 1980-97. In panel (A), both series have the common starting point given the adjustment for 1980. While the BEA series trends upwards smoothly, our constructed series clearly trends downwards and is very volatile. The average values for BEA series and our constructed series are 0.119 and 0.104 respectively. A look at the panel (B) in figure (3.4) reveals that our constructed series picks up the volatility of the financial component arising from the monetary policy changes discussed earlier. One important finding of this exercise is that the fall in the relative price ratio is very rapid in the service sector which is the prime factor in creating a downward trend in the "Adj.Wt.RUC".[19] The relative price ratio falls at the rate of 2.12% annually for 1980-97. Here it is worth noting Greenwood et.al. (1997) who find the rate of fall in the relative price ratio of "equipment" to be 3.21% annually for 1954-90. Greenwood et.al. (1997) argue that improving technology in the "equipment" producing industries reduces the price of "equipment" in terms of the final good causing a huge increase in the accumulation of "equipment". The authors define this improvement in technology in "equipment" producing industries as "Investment Specific Technological Change (ISTC)". In their model, growth rate of "ISTC" is identified as the rate of decline in the relative price ratio which is 3.21%. Even though, our investment price deflator is for both "equipment

[19]The one time fall in the tax component post 1987 due to the cut in federal corporate income tax rate to 34% also contributes to the downward trend of our constructed series.



(A)



(B)

Figure 3.4: **BEA Implied Real User Cost and Adjusted Weighted Real User Cost (Services) (1980-97)**

and software" and "structures", we find a large drop in the relative price ratio at a rate of 2.12% which implies for very high capital accumulation.[20] Given this, contrary to the BEA implied series, our constructed series on the real user cost displays a negative growth which is the major source of divergence between the primal and dual measures of MFP growth. This negative growth of real user cost implies a smaller role for MFP growth and a larger

[20] Jorgenson et.al. (2005) find that IT-producing industries have experienced a productivity growth leading to rapid fall in the price of IT equipment and softwares leading to a economy-wide surge in IT related investments. For the service sector industries, they find that there is not only a huge increase in the IT-investments but also rapid accumulation of non-IT investment leading to rapid increase in capital accumulation for the period 1977-1995.

role for capital accumulation in explaining the growth of service sector.

Table 3.4: **Growth Rate of Real User Cost of Capital and Real Capital Stock (US) (1980-97).** Note: The presented numbers are in percentages.

	BEA_RUC	Adj.Wt.RUC	BEA K	Estimated K
Manufacturing	3.24	2.12	1.37	2.37
Services	1.19	-0.91	3.02	5.11

Implication for Real Capital Stock: Table (3.4) presents the average annual growth rates for real user cost of capital and real capital stock series. First two columns refer to the growth rates of "BEA_RUC" and "Adj.Wt.RUC". Last two columns present the growth rates for the BEA produced estimates and our constructed series on the real capital stock. Our constructed series of capital stock at the national level is obtained by summing over the state level nominal measures and then deflating it by the national price index for the capital stock.[21]

For 1980-97, "BEA_RUC" grows annually at 3.24% where as the growth rate of "Adj.Wt.RUC" is around 2.12.% for the manufacturing sector. As the figures suggest, our constructed series results in a lower growth rate compared to the same of BEA, hence our constructed counterfactual real capital stock experiences a higher growth rate of 2.37% as opposed to the BEA's 1.37%. But our constructed series generates a positive growth of real user cost capital implying a higher MFP growth. Compared to "BEA_RUC", our constructed real user cost for the service sector experiences negative growth due to the rapid fall of the relative price ratio resulting from the "ISTC". Given this, the growth rate of the counter factual real capital stock is 5.11 % as opposed to a 3.02% growth rate of the BEA produced estimates. Our results are in accordance with the results of Greenwood et. al (1997) in presenting a higher growth of capital stock due to the "ISTC".[22]

[21]State-sector specific real capital stock is $K_{i,s,t} = \frac{(1-\alpha_{L,i,s,t})Y_{i,s,t}}{Adj\_RUC_{i,s,t}}$. State-sector specific real capital stock is converted to its nominal value using the respective price deflator for the capital stock.

[22]In a calibrated model, they predict a higher growth for equipments compared to the BEA produced estimates, hence a greater role for "ISTC".

Real User Cost for State Manufacturing and Services: Before discussing the growth performance of the real user cost at the state level, we briefly examine the state level real user cost for both sectors which forms the base to the growth accounting exercise. With perfect mobility of capital goods and integrated financial markets, one would expect the cost of investment in capital to equalize across states in US. Nevertheless, differences between them can arise because of the liberal tax policies by some states to boost the state investment prospects or due to the compositional differences leading to differences in the relative price ratio of investment goods.

Table 3.5: **Average Adjusted Real User Cost and Components of Real User Cost (1980-97)**

	Manufacturing				Services			
	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$
US	0.187	1.014	0.136	1.114	0.104	1.277	0.123	1.199
Alabama	0.200	1.026	0.134	1.108	0.102	1.260	0.125	1.174
Alaska	0.226	1.135	0.132	1.121	0.091	1.125	0.120	1.221
Arizona	0.157	0.790	0.138	1.101	0.103	1.278	0.121	1.203
Arkansas	0.207	1.052	0.134	1.116	0.102	1.248	0.124	1.190
California	0.190	0.950	0.137	1.118	0.106	1.289	0.123	1.214
Colorado	0.207	1.047	0.137	1.099	0.102	1.259	0.123	1.190
Connecticut	0.206	1.020	0.136	1.131	0.108	1.309	0.120	1.239
Delaware	0.245	1.232	0.135	1.124	0.107	1.344	0.114	1.255
DC	0.267	1.356	0.137	1.107	0.117	1.386	0.130	1.186
Florida	0.216	1.074	0.140	1.090	0.103	1.278	0.122	1.193
Georgia	0.234	1.179	0.136	1.112	0.103	1.252	0.126	1.186
Hawaii	0.272	1.317	0.147	1.073	0.102	1.278	0.119	1.209
Idaho	0.159	0.802	0.136	1.112	0.103	1.259	0.124	1.196
Illinois	0.190	0.951	0.136	1.116	0.105	1.286	0.123	1.201
Indiana	0.199	1.001	0.135	1.122	0.103	1.276	0.122	1.200
Iowa	0.183	0.922	0.134	1.129	0.106	1.292	0.123	1.210

Table 3.5: **(Contd.)**

	Manufacturing				Services			
	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$
Kansas	0.221	1.132	0.134	1.108	0.101	1.244	0.124	1.183
Kentucky	0.184	0.936	0.133	1.121	0.104	1.265	0.124	1.193
Louisiana	0.222	1.148	0.131	1.111	0.105	1.270	0.127	1.179
Maine	0.226	1.132	0.137	1.118	0.105	1.275	0.123	1.206
Maryland	0.230	1.129	0.142	1.097	0.105	1.287	0.123	1.199
Massachusetts	0.185	0.925	0.136	1.125	0.109	1.316	0.123	1.212
Michigan	0.211	1.080	0.134	1.111	0.104	1.293	0.124	1.173
Minnesota	0.200	1.001	0.135	1.127	0.107	1.282	0.124	1.216
Mississippi	0.204	1.041	0.134	1.112	0.100	1.239	0.124	1.186
Missouri	0.218	1.109	0.136	1.107	0.103	1.266	0.125	1.176
Montana	0.176	0.878	0.137	1.103	0.101	1.237	0.123	1.193
Nebraska	0.201	1.014	0.136	1.111	0.102	1.257	0.123	1.197
Nevada	0.186	0.926	0.143	1.071	0.113	1.370	0.130	1.147
New Hampshire	0.166	0.829	0.136	1.118	0.105	1.300	0.121	1.214
New Jersey	0.225	1.121	0.137	1.120	0.104	1.280	0.122	1.208
New Mexico	0.136	0.712	0.130	1.110	0.102	1.255	0.123	1.194
New York	0.224	1.115	0.137	1.122	0.102	1.251	0.120	1.231
North Carolina	0.240	1.214	0.135	1.121	0.103	1.265	0.124	1.193
North Dakota	0.187	0.944	0.136	1.100	0.105	1.266	0.127	1.184
Ohio	0.198	0.997	0.134	1.128	0.106	1.288	0.124	1.203
Oklahoma	0.195	1.008	0.132	1.111	0.103	1.261	0.125	1.183
Oregon	0.155	0.780	0.136	1.117	0.104	1.277	0.124	1.197
Pennsylvania	0.199	0.996	0.135	1.127	0.108	1.305	0.124	1.211
Rhode Island	0.202	1.012	0.136	1.123	0.107	1.317	0.122	1.213
South Carolina	0.202	1.020	0.135	1.115	0.103	1.254	0.125	1.190
South Dakota	0.179	0.929	0.135	1.090	0.101	1.281	0.122	1.174
Tennessee	0.209	1.058	0.135	1.116	0.106	1.280	0.127	1.182

Table 3.5: **(Contd.)**

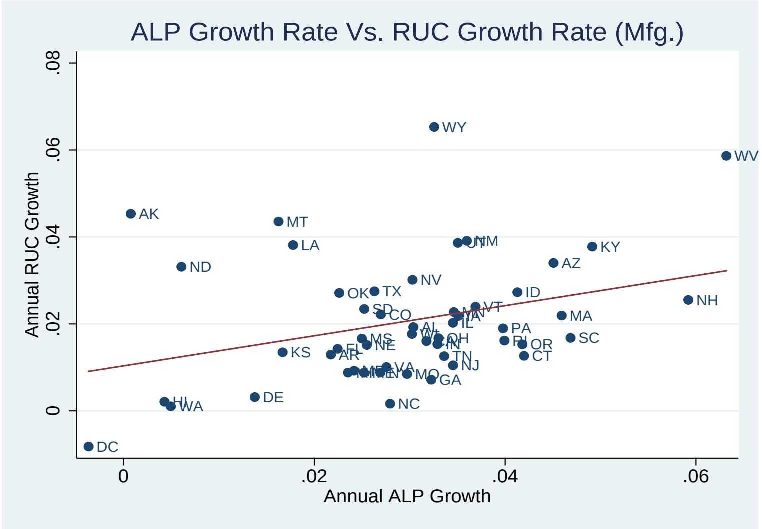
	Manufacturing				Services			
	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$
Texas	0.193	0.999	0.134	1.095	0.102	1.267	0.125	1.164
Utah	0.188	0.958	0.135	1.103	0.103	1.268	0.124	1.182
Vermont	0.169	0.846	0.136	1.117	0.105	1.296	0.122	1.204
Virginia	0.242	1.220	0.136	1.108	0.102	1.265	0.122	1.195
Washington	0.233	1.182	0.138	1.091	0.102	1.277	0.124	1.166
West Virginia	0.150	0.758	0.133	1.121	0.102	1.245	0.124	1.197
Wisconsin	0.193	0.972	0.134	1.125	0.105	1.299	0.122	1.206
Wyoming	0.177	0.918	0.131	1.098	0.091	1.169	0.121	1.172

Table (3.5) represents the state-wise averages of adjusted real user cost of capital and its components for both sectors. The first four columns in the table correspond to the results for the manufacturing sector and the rest of the columns report the results for the service sector. For US manufacturing sector, the averages are 0.187, 1.014, 0.136 and 1.114 for the adjusted real user cost, relative price ratio, financial component and the tax component respectively. The standard deviation for the adjusted real user cost across states is 2.8%. Among the three components, the financial component displays the lowest variation of 0.3% since the interest rate is same across US. It is followed by the tax component with a moderate variation of 1.3% but the most of the variation in adjusted real user cost can be attributed to the relative price ratio with a variation of 13.9%. This variation in the relative price ratio is rooted in the compositional differences of the manufacturing sector across states. New Mexico, West Virginia, Oregon, Idaho, Arizona and New Hampshire experience very low average adjusted real user costs resulting from very low relative price ratios. The relative price ratio for all these states is below one. DC, Hawaii, Delaware, Virginia and North Carolina have very high adjusted real user costs as a result of high relative price ratios. As described earlier, the tax component reflects the tax incentives given by the government in terms of lower corporate income taxes and higher depreciation deductions. In presence of these incentives, the tax component displays a lower value putting a downward pressure on the adjusted real user cost of capital. Nevada, South Dakota, Hawaii, Florida, Washington, Texas and Wyoming are the states with the lowest tax components. While tax benefit is rendered to Nevada, South Dakota, Washington, Texas and Wyoming through the absence of state corporate income taxation, Hawaii and Florida enjoy the tax benefit through higher present value of depreciation deductions (z) due to higher depreciation rates.[23]

US service sector has an average adjusted real user cost of 0.104. The relative price ratio, financial and tax components are 1.277, 0.123 and 1.199 respectively. The standard deviation of the real user cost across states is very low at 0.4%. The standard deviations for the relative price ratio, financial component and the tax component are 3.9%, 0.3% and 1.9% respectively. The very low variation for the financial component can attributed to the equality of interest rates across states. The variation observed in the adjusted real user cost can be attributed mostly to the variations in the relative price ratio component and the tax component. DC, Nevada, Pennsylvania and Massachusetts are the states with higher adjusted real user cost of capital. DC and Nevada are the two states with larger share of SGDP in "services" industry catering to business services, amusement, motion pictures, education, legal services etc. The investment deflator for these industries is higher compared to the other industries in the service sector. Given this, DC and Nevada experience higher relative price ratios, hence higher real user cost. Pennsylvania and Massachusetts are the states with higher state corporate income tax rates which lead to larger tax components leading to larger real user cost of capital.

Real User Cost Growth for State Manufacturing and Services: If the ALP growth is mostly driven by capital accumulation, one would expect the states with very high ALP growth to produce large decline in the real user cost of capital. So, during the period of productivity slowdown when MFP growth has a minimal role in explaining the growth, one

[23]Though Texas does not have a corporate income tax rate, it imposes a franchise tax of 4.5% on businesses. But our paper does not consider that. South Dakota does not impose state corporate taxes on businesses though it imposes a tax on financial institutions.



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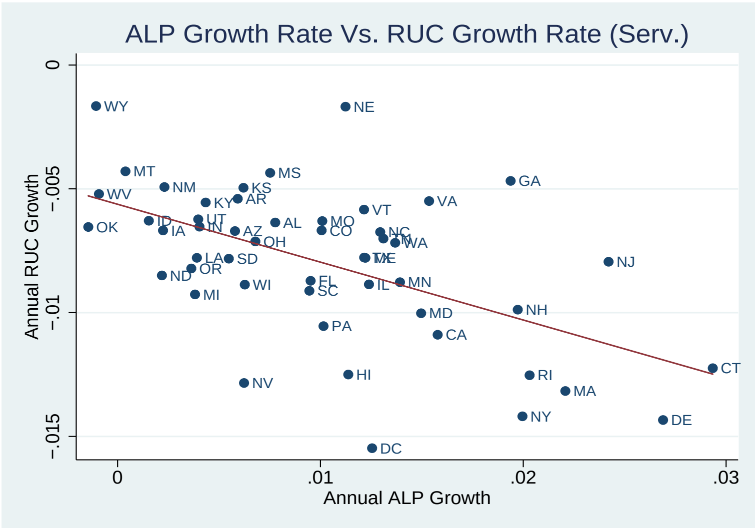


(B)

Figure 3.5: **ALP Growth Vs. Real User Cost Growth (1980-1997)**

would expect a negative relationship between the ALP growth and real user cost growth. But in the presence of a stronger role for MFP growth in explaining the ALP growth, states with high ALP growth will associate themselves with high factor price growth. Hence, one would expect a positive association between the ALP growth and real user cost growth.

The case of manufacturing sector is presented in figure (3.5) panel (A). We see a positive relationship between the ALP growth and real user cost growth indicating a stronger role of MFP growth in driving ALP growth. As discussed earlier, even though 1980-97 was a period marked by the productivity slowdown, the manufacturing sector experienced a higher MFP growth (Triplett and Bosworth, 2001 and Jorgenson et.al., 2005). Figure (3.5) panel (A) demonstrates that states with higher ALP growth rates like West Virginia, Massachusetts, Arizona and Kentucky associate with higher growth rates of real user cost of capital, hence a stronger role for MFP growth. Oil rich states like Alaska, Louisiana, Wyoming produce very high real user cost growth rates. This can be attributed to the fact that during early 1980s the oil price was very high causing the SGDP deflator of the mining industry to be inflated. With a larger share of mining industry, these states experience very high SGDP deflators for the manufacturing sector in early 1980s and hence very low real user costs. As the oil price starts to stabilize, these states experience higher growth in real user cost as the SGDP deflator starts falling. Hawaii, Delaware, Washington, Kansas are the states that demonstrate lower growth for both ALP and real user cost. A coefficient of variation (CV) of 70% for the real user cost growth indicates the presence of wide variation across states. In the literature, economists tend to assume the growth rate of the real user cost to be zero or a redundant role for it if the growth rates equalize across states (Ciccone and Peri, 2006 and Iranzo and Peri, 2009). One can conclude that assuming a redundant role for the real user cost is unwarranted in evidence of wide variability in the growth rates of the real user cost across states.

Figure (3.5) panel (B) presents the case of the service sector. A strong negative relationship between the ALP growth and real user cost growth is evident from the figure. One can infer a larger role for capital accumulation and a minimal role for MFP growth in driving ALP growth given this negative relationship. This conclusion can be corroborated given the productivity slowdown which affected the service sector industries till 1995 (Triplett and Bosworth, 2001 and Jorgenson et.al., 2005). A close look at the figure reveals that states like Connecticut, Delaware, Massachusetts, Rhode Island, New York and New Jersey with very high ALP growth associate themselves with larger fall in the real user cost of capital implying very high growth for capital accumulation. States like Oklahoma, West Virginia, Montana, Wyoming lie in the lower end of the ALP growth and real user cost growth relationship. One interesting fact is that all the states experience negative growth rate for the real user cost due to the rapidly falling relative price ratio. This infers a major role for rapid capital accumulation through "ISTC" in driving the service sector growth. Similar to the manufacturing sector, we find wide variation in real user cost growth across states.

3.4.1.4 Real Wage Growth

US Manufacturing and Services: Table (3.6) presents our results on real wage growth for US. Our measure of real wage grows at the rate of 2.13% and 0.96% annually for the manufacturing and service sectors respectively. The growth literature suggests that in the presence of a constant labor income share, ALP and real wage should grow at the same rate. In US, there has been a concern that real wage growth is not keeping up with ALP growth, i.e., the benefits of increased productivity are not accrued to the labor. Bosworth et.al. (1994) and Dew-Becker and Gordon (2005) provide evidence for this at the non-farm business sector of US. Although our real wage growth numbers fall behind the ALP growth numbers for 1980-97, the gap between them is not very large. In this regard, there is consensus in the existing literature that the measure of real wage growth is sensitive to the choice of price deflator (Bosworth et. al., 1994 and Dew-Becker and Gordon, 2005). While economists use GDP deflator for calculating ALP growth, deflators like Consumer Price Index-Urban (CPI-U) and Personal Consumption Expenditure (PCE) are used to construct the measures of real wage growth. As a robustness check, we construct the real wage growth measures using deflators for CPI-U and PCE. With the use of CPI-U, the average annual growth rates are -0.07% and 0.43% for the manufacturing and service sectors respectively. With the use of PCE deflator, the annual real wage growth rates are 0.3% and 0.8% for the manufacturing and service sectors respectively. It can be clearly visualized that opting for these deflators creates a very wide gap between ALP growth and real wage growth. This provides evidence that our results are in the line of the existing literature. Bosworth et.al. (1994) and Dew-Becker and Gordon (2005) find that the use of GDP deflator to calculate real wage growth provides higher measured values compared to the use of CPI-U and PCE.

The measures of real wage growth for our analysis are derived from the IPUMS-CPS data set. This micro data set is top coded and allows us to adjust for "quality" based on education and gender. With these two factors, the measure of real wage growth can be a source of divergence between the primal and dual measures of MFP growth if this

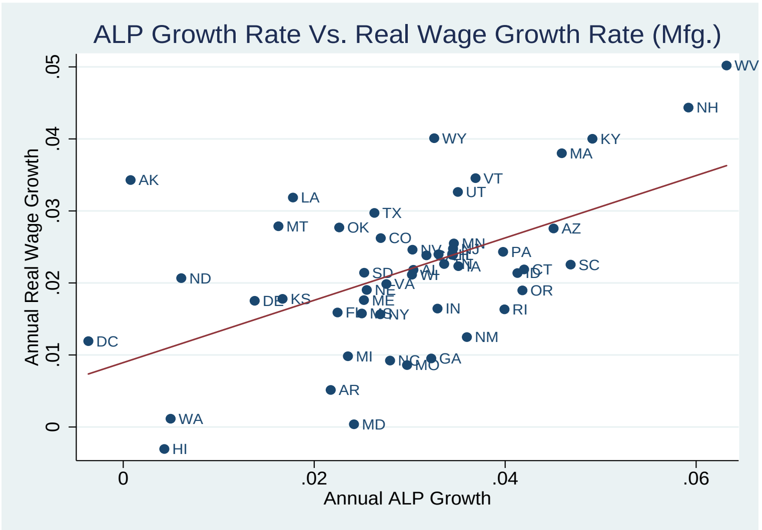
Table 3.6: **Average Annual Labor Productivity Growth Rate and Real Wage Growth Rate (US) (1980-97).** Note: ALPG=Average labor productivity growth rate for US, RWG=Real wage growth rate for US, St.Wt.= State weighted measures for US, CWG=Compensation per full time worker growth rate, RWG(CPI-U)=Real wage growth rate using Consumer Price Index-Urban, RWG(PCE)= Real wage growth rate using the deflator for Personal Consumption Expenditure (PCE). The presented numbers are in percentages.

	Manufacturing	Services
ALPG	2.99	1.24
ALPG (St.Wt.)	3.08	1.24
RWG	2.04	0.92
RWG(St.Wt.)	2.13	0.96
CWG	2.47	1.12
CWG (St.Wt.)	2.54	1.17
RWG (CPI-U)	-0.07	0.43
RWG (PCE)	0.3	0.8

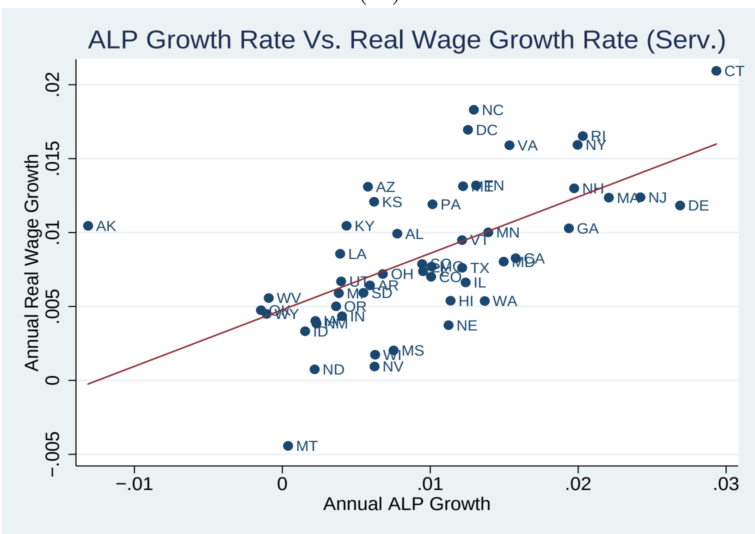
measure differs from the real wage growth measure derived from the BEA. The measure of real wage growth based on the "compensation per full time worker" data from the BEA is not top coded and does not undergo "quality adjustment", so the implied MFP growth using this data is directly comparable to the primal accounting results.[24] It is evident from table (3.6) that the state-weighted real wage growth measures based on the "compensation per full time worker" provide marginally higher growth rates of 2.54% and 1.17% for the US manufacturing and service sectors respectively. Dew-Becker and Gordon (2005) provide evidence that the median income in US has not kept up with the productivity growth but the average wage has kept up with it as most of the productivity gain is rendered to the top 10% of the income distribution. While the "compensation of employee" includes the top 10% of the income distribution, the IPUMS-CPS data set is top coded, therefore results in lower real wage growth. We use the measures of real wage growth based on "compensation per full time worker" to construct the dual measures of MFP growth. These results are reported in table (3.1) and (3.2) respectively for the manufacturing and service sectors. The resulting MFP growth rate of 2.42% for the manufacturing sector is higher than that derived from IPUMS-CPS, and is also close to the primal growth rate of 2.65%. For the service sector, the measure of MFP growth experiences a growth rate of 0.38% annually which is far below

[24]The primal accounting exercise using the BEA data on persons engaged in production and capital stock does not undertake any quality adjustments based on the labor groups and type of capital goods.

the primal growth rate of 1.13%. Even using the real wage growth measure from the BEA does not bridge the gap between the primal and dual measures of MFP growth, so we can conclude that the inconsistency between the constructed real user cost and the implied real user cost from the BEA is the source of divergence between the two.



(A)



(B)

Figure 3.6: **ALP Growth Vs. Real Wage Growth (1980-97)**

State Manufacturing and Services: Figure (3.6) (A) and (B) plot the average annual ALP growth against the average annual real wage growth for the manufacturing and service sectors respectively. The existence of a strong positive relationship between the two is evident for both sectors. This is in accordance with the fact that the gain to productivity should be accrued to the worker in terms of higher real wage growth, hence a higher growth in ALP should associate with a higher growth in real wage. For the manufacturing sector, states with very high ALP growth: West Virginia, New Hampshire, Kentucky and Massachusetts produce very high real wage growth for workers. Washington, Maryland, Arkansas and Hawaii produce very low real wage growth for the manufacturing sector. As discussed earlier, there has been a concern that real wage growth is not matching up to the ALP growth in US. A look at the states suggests that for the manufacturing sector, the average real wage growth rate for 33 states lies below the 75% of their average ALP growth rate. While Alaska, North Dakota, Delaware, Montana, Louisiana, Wyoming, Oklahoma, Texas and Kansas experience a real wage growth rate higher than the ALP growth rate, the real wage growth rates for Maryland, Washington, Arkansas, Missouri, Georgia, North Carolina and New Mexico remain below the 40% of their ALP growth rates. For the service sector, the service sector rich states like Connecticut, New York, New Jersey, Rhode Island and Massachusetts experience higher real wage growth rates associated with higher ALP growth rates. Montana, Wyoming, North Dakota and Idaho are the states that represent the lower end of this relationship. As opposed to the manufacturing sector in case of the service sector, half of the states manage to achieve real wage growth rates higher than the 75% of the ALP growth rates. But this can be attributed to the fact that most of the states experience very low ALP growth during this time period of productivity slowdown. For example, states like Kentucky, Louisiana, Idaho, Iowa, Utah, New Mexico, Michigan and Oregon experience real wage growth rates higher than 100% of the ALP growth rates, but this is because all these states associate themselves with ALP growth rates below 0.5%. With this one can conclude that the depressed MFP growth rates across the states in the service sector root from the negative real user cost growth rates which implies for greater role for capital accumulation.

The discussion on the SIC classification can be concluded citing Hsieh (2002) and Aiyar and Daalgard (2005) who argue that the primal and dual accounting measures of MFP growth would differ if the observed real factor price is inconsistent from those implied by the national accounts. For 1980-97, the dual measures of MFP growth for both sectors differ from the primal measures with the service sector experiencing the maximum deviation. Upon investigation, we find that the inconsistency of our constructed real user cost series with that of BEA is the source of this divergence. While the declining tax component and relative price ratio contribute in keeping the constructed real user cost low for the manufacturing sector, it is the rapid decline in the relative price ratio which generates a negative growth rate for the real user cost of the service sector. This rapid fall in the relative price ratio is not captured by the BEA.

3.4.2 North American Industrial Classification System (NAICS) (1998-2007)

3.4.2.1 Multi-Factor Productivity Growth

US Manufacturing and Services: Since 1995, the US economy has experienced a surge in productivity. Stiroh (2002) provides evidence of acceleration in labor productivity not only in IT-producing industries but also in IT-using industries. In a study, Triplett and Bosworth (2002) find that the service sector industries experience an accelerated MFP growth after 1995. We report the dual measures of MFP growth for both sectors for 1998-2007 in table (3.7).[25] Contrary to the literature, the ALP growth rate declines to 1.52% for the manufacturing sector and it experiences a negative MFP growth rate of -0.95%. The primal measure of MFP growth produces a contradictory result where the MFP growth rate declines to 0.45%, but remains higher than that of the dual accounting measure. Although the service sector experiences an accelerated ALP growth of 1.77%, this growth rate remains much lower when compared to the existing literature. Jorgenson et.al. (2008) documents a 3.09% growth rate for the ALP of the private economy for 2000-2005. Given the larger share of service sector in the private economy, one would expect a much higher ALP growth rate. The service sector experiences an annual MFP growth rate of -0.17% originating from a negative real user cost growth and a marginal real wage growth derived from the IPUMS-CPS data set which is much lower than the primal growth rate of 1.01%. For further insight, we

[25]In NAICS for the manufacturing sector, the state weighted measures deviate from their direct national measures as the imputation of labor income share for 1998-2000 creates a bias in the weighting and secondly, mining and construction industries have missing data problem in wage and salary employment for 2001 and 2002 for some of the states, while calculating the labor income share these industries are dropped which adds to this bias.

report the results for 1998-2002 and 2002-2007 separately in table (3.8) to verify whether our price based measures are supporting the post 1995 productivity revival in US. For 1998-2002, both sectors show higher growth rates for ALP. The MFP growth rates are 1.91% and 1.38% contributing 0.57% and 0.78% to ALP growth for the manufacturing and service sectors respectively. This is consistent with the productivity recovery in US. The higher MFP growth rates result from the higher factor price growth rates. During 2002-2007 both sectors experience negative MFP growth rates originating from the negative real factor price growth rates which contradict the productivity revival literature.

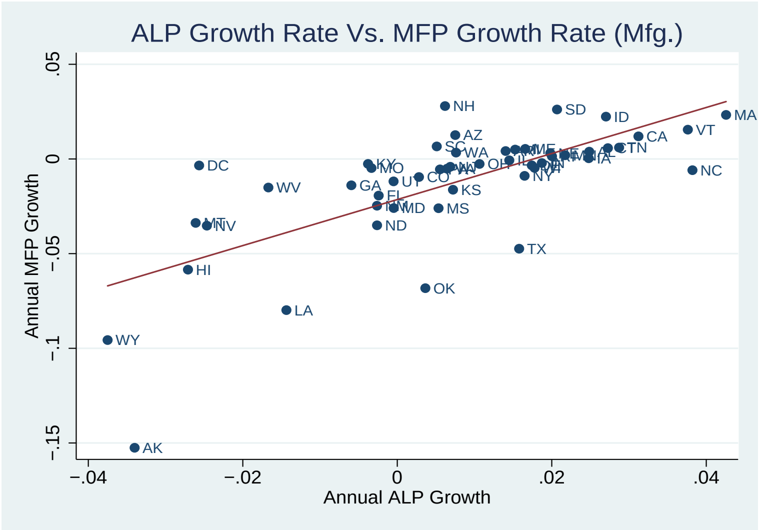
Table 3.7: **Average Annual MFP Growth Rate (US) (1998-2007).** Note: The presented numbers are in percentages. ALPG=Average labor productivity growth rate, RWG=Real wage growth rate, RUCG=Real user cost growth rate, MFPG=Multi-factor productivity growth rate, Primal=Our primal measures of MFP growth rate calculated using the data from BEA.

	Manufacturing			Services		
	St.Wt.	US	Primal	St.Wt.	US	Primal
ALPG	1.52	1.23	1.25	1.77	1.78	1.8
RWG	0.00	-0.51		0.69	0.67	
RUCG	-3.16	-2.47		-1.60	-1.59	
MFPG	-0.95	-1.08	0.45	-0.17	-0.19	1.01

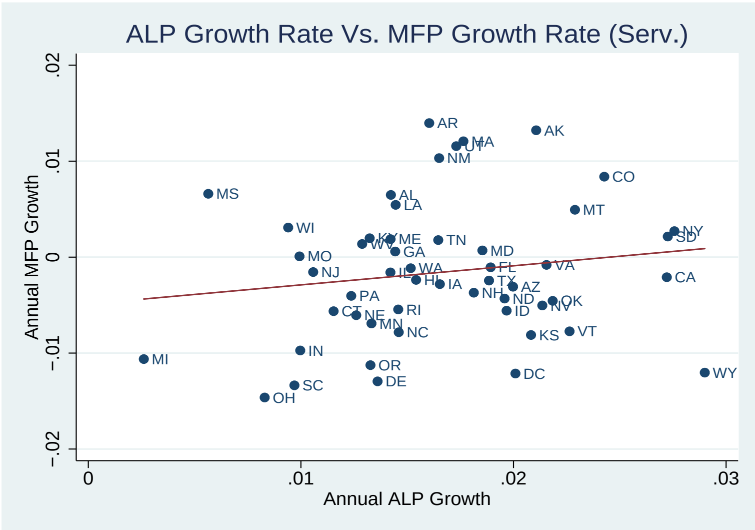
Table 3.8: **Average Annual MFP Growth Rate (US) (1998-2007).** Note: The presented numbers are in percentages. ALPG=Average labor productivity growth rate, RWG=Real wage growth rate, RUCG=Real user cost growth rate, MFPG=Multi-factor productivity growth rate.

	Manufacturing				Services			
	1998-02		2002-07		1998-02		2002-07	
	St.Wt.	US	St.Wt.	US	St.Wt.	US	St.Wt.	US
ALPG	3.33	3.23	0.07	-0.37	1.75	1.76	1.79	1.8
RWG	2.28	2.28	-1.82	-2.74	1.97	1.94	-0.32	-0.35
RUCG	1.00	1.56	-6.48	-5.69	0.37	0.39	-3.19	-3.18
MFPG	1.91	2.08	-3.24	-3.62	1.38	1.37	-1.42	-1.43

State Results: Figure (3.7) panel (A) and (B) display the relationship between ALP growth and MFP growth at the state level for the manufacturing and service sectors respectively. Although figure (3.7) panel (A) displays a positive relationship between ALP growth and MFP growth for the manufacturing sector, more than 30 states experience ALP



(A)



(B)

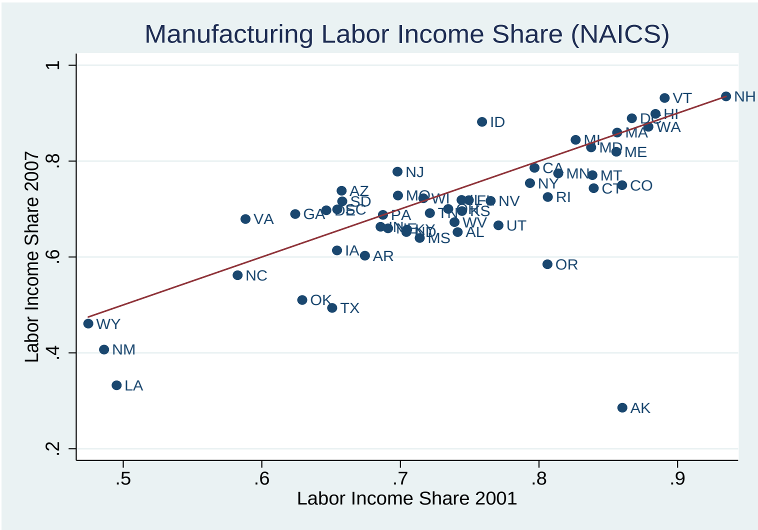
Figure 3.7: **ALP Growth Vs. MFP Growth (1998-2007)**

growth rates lower than 1% and negative MFP growth rates. A similar finding is presented for the service sector in figure (3.7) panel (B). Although we find a weak positive relationship between the two, more than 30 states experience negative MFP growth rates implying suppressed factor price growth rates.

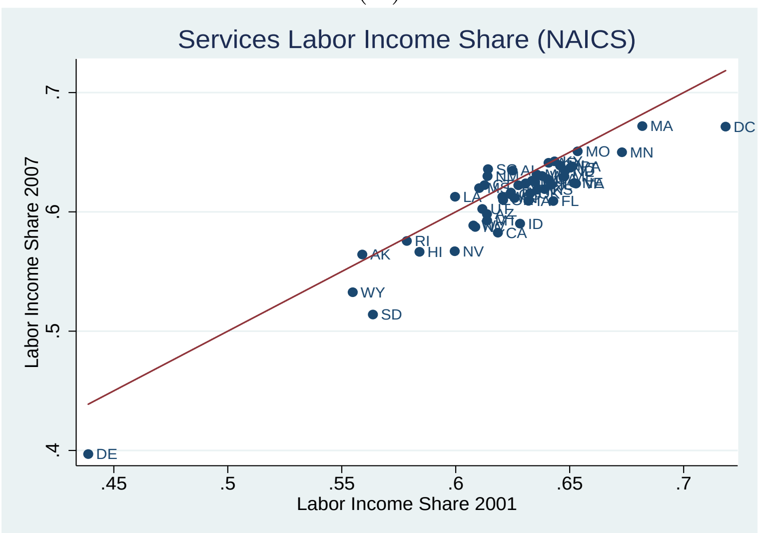
In the subsequent sections, we analyze individual components of MFP growth to determine the reasoning behind the suppressed real factor price growth and hence the huge deviations from the primal MFP growth measures.

3.4.2.2 Labor Income Share

Figures (3.8) (A) and (B) plot the state-wise labor income share for 2001 against the same for 2007 for the manufacturing and service sectors respectively.[26] The variations in labor income share is higher in the manufacturing sector compared to the service sector and both sectors experience a marginal decline in labor income share in 2007 as compared to 2001.



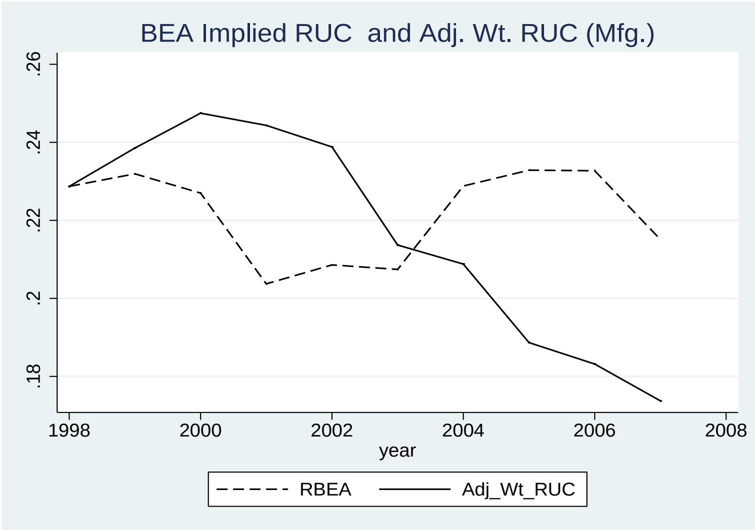
(A)



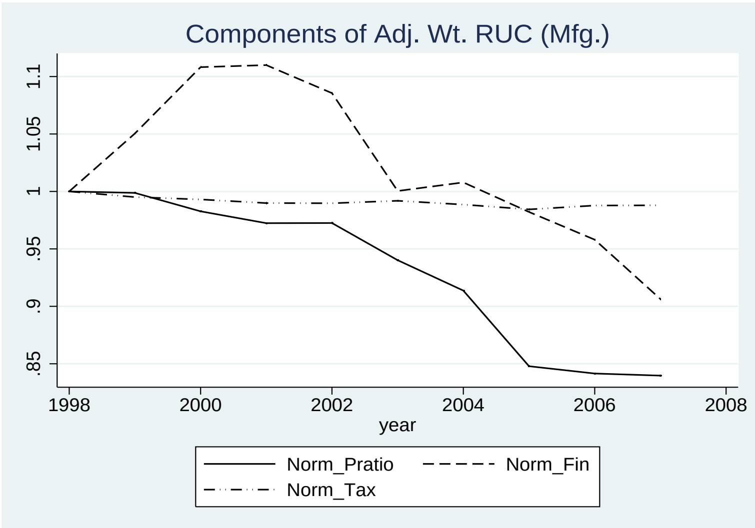
(B)

Figure 3.8: **Labor Income Share (1998-2007)**

[26]Since the labor income share of 1998-2000 for a state is imputed as the average of labor income share of 2001-2007 for that state, for NAICS we plot the labor income share of 2001 against labor income share of 2007.



(A)

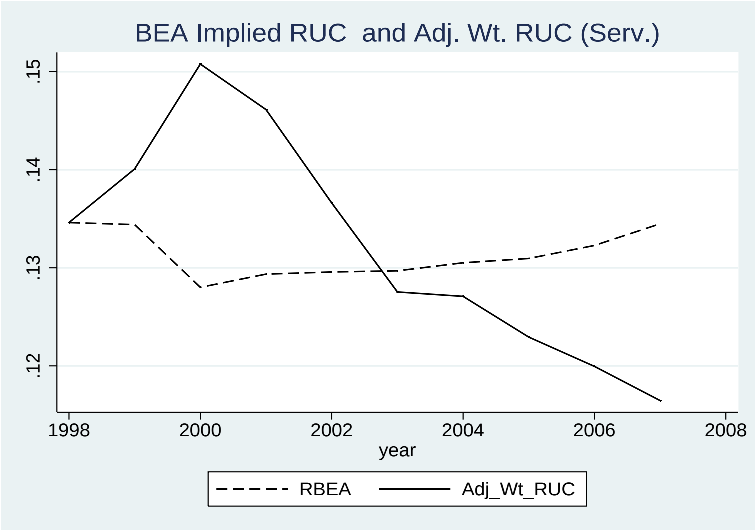


(B)

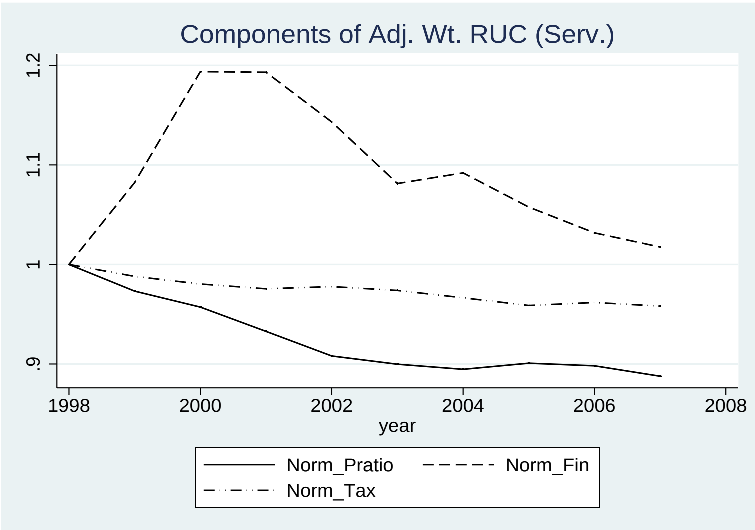
Figure 3.9: **BEA Implied Real User Cost and Adjusted Weighted Real User Cost (Manufacturing) (1998-07)**

3.4.2.3 Real User Cost of Capital

US Manufacturing and Services: We contrast our constructed real user cost with the BEA implied real user cost to understand the source of divergence between the primal and dual measures of MFP growth. Figure (3.9) panel (A) and (B) represent the “Adj.Wt.RUC” against the “BEA_RUC” and its components for the manufacturing sector respectively. In panel (A), both series have the same starting point given the adjustment applied for 1998. “BEA_RUC” fluctuates around an average value of 0.22. But our constructed series “Adj.Wt.RUC” clearly trends downwards throughout with an average value of 0.217.



(A)



(B)

Figure 3.10: **BEA Implied Real User Cost and Adjusted Weighted Real User Cost (Services) (1998-07)**

Initially, "Adj.Wt.RUC" remains higher compared to the BEA implied series because of a rising financial component but post 2001, the nominal interest rate declines as a result of an easing monetary policy due to 2001 recession causing the financial component to decline. But the fall in "Adj.Wt.RUC" is much more rapid than the fall in the financial component due to the pronounced fall in the relative price ratio. The rapid fall in the relative price ratio is attributed to the sharp increase in the GDP deflator of the manufacturing sector. This shock to GDP deflator originates from the mining and construction industries where the GDP deflators experience rapid increase post 2002.[27]

Figure (3.10) panel (A) and (B) represent "Adj.Wt.RUC" against "BEA_RUC" and its components for the service sector respectively. The averages are 0.13 and 0.132 for "BEA_RUC" and "Adj.Wt.RUC" respectively. While "BEA_RUC" remains stable around the average value, "Adj.Wt.RUC" starts falling rapidly after the rapid fall in the financial component post 2001 recession. The fall is acerbated due to the fall in the relative price ratio as well which results from the rising GDP deflators of the industries inside the service sector. Even the tax component shows a decline, hence adding to the downward trend of the constructed "Adj.Wt.RUC". The surge in IT investments which possess lesser life span (Schaller, 2006), leads to a higher depreciation rate for the service sector. This leads to a rise in the present value of depreciation deductions, hence a falling tax component.

One can clearly infer here that 1998-2007 is a very short time span which is affected by adverse price shocks and business cycle fluctuations. These short run shocks contribute immensely in creating a downward trend in the constructed real user cost of both sectors and act as a source of divergence from the BEA implied real user cost. As a result of the sharp fall in the real user cost in both sectors, our constructed counter factual real capital stock grows at a faster rate than those of BEA. This is presented in table (3.9).

Table 3.9: **Growth Rate of Real User Cost of Capital and Real Capital Stock (US) (1998-07).** Note: The numbers are in percentages.

	BEA_RUC	Adj.Wt.RUC	BEA K	Estimated K
Manufacturing	-0.68	-3.05	1.87	4.49
Services	-0.01	-1.61	3.59	5.00

Real User Cost Growth for State Manufacturing and Services: Before presenting the real user cost growth results at the state level, we briefly discuss our constructed real user costs here. Table (3.10) presents the average values for the adjusted real user cost and its components for both sectors. The standard deviation for the manufacturing sector indicates that there are 1.6%, 3.7%, 1.4% and 1.2% variations across states for the adjusted real user

[27]Post 2002, rapidly increasing oil price contributes to an inflated GDP deflator for the mining industry.

cost, relative price ratio, financial component and the tax component respectively. One of the striking feature of the NAICS result is that for most of the states, the relative price ratio lies below one given the price shocks to SGDP deflators of mining and construction industries. For the service sector, the variation for real user cost across states is 0.5%. The variations for the price ratio, financial component and the tax component across states have subdued to 0.7%, 0.9% and 1.3% respectively. The relative price ratio for all the states lies below one. The variation of financial component increases during 1998-2007 due to the rising depreciation rate resulting from the accumulation of IT-equipment which has lesser life span. The tax component shows similar variability to the previous time period.

Table 3.10: **Average Adjusted Real User Cost and Components of Real User Cost (1998-2007)**

	Manufacturing				Services			
	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$
US	0.222	0.950	0.166	1.036	0.132	0.967	0.156	1.070
Alabama	0.220	0.957	0.165	1.036	0.129	0.966	0.153	1.069
Alaska	0.177	0.988	0.119	1.072	0.125	0.971	0.143	1.099
Arizona	0.233	0.975	0.173	1.028	0.129	0.971	0.151	1.080
Arkansas	0.220	0.951	0.165	1.041	0.128	0.966	0.149	1.083
California	0.230	0.970	0.171	1.035	0.132	0.972	0.155	1.075
Colorado	0.213	0.921	0.167	1.027	0.136	0.974	0.161	1.060
Connecticut	0.224	0.953	0.169	1.039	0.136	0.959	0.163	1.066
Delaware	0.225	0.930	0.175	1.030	0.140	0.940	0.172	1.061
DC	0.232	0.868	0.200	0.999	0.149	0.942	0.188	1.028
Florida	0.230	0.908	0.186	1.014	0.127	0.972	0.148	1.079
Georgia	0.224	0.946	0.171	1.033	0.135	0.972	0.159	1.066
Hawaii	0.231	0.872	0.197	1.002	0.119	0.981	0.134	1.105
Idaho	0.244	1.017	0.173	1.030	0.130	0.969	0.153	1.076
Illinois	0.224	0.946	0.171	1.035	0.136	0.962	0.162	1.063
Indiana	0.225	0.976	0.165	1.045	0.127	0.963	0.148	1.088

Table 3.10: **(Contd.)**

	Manufacturing				Services			
	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$
Iowa	0.225	0.968	0.166	1.046	0.130	0.955	0.153	1.087
Kansas	0.213	0.931	0.164	1.038	0.131	0.965	0.156	1.067
Kentucky	0.222	0.981	0.162	1.045	0.129	0.965	0.150	1.083
Louisiana	0.189	0.931	0.142	1.053	0.126	0.964	0.148	1.080
Maine	0.229	0.949	0.174	1.032	0.125	0.968	0.144	1.095
Maryland	0.229	0.915	0.184	1.018	0.132	0.969	0.157	1.068
Massachusetts	0.239	0.996	0.173	1.034	0.138	0.963	0.164	1.063
Michigan	0.233	1.005	0.167	1.035	0.132	0.964	0.158	1.058
Minnesota	0.229	0.968	0.170	1.038	0.134	0.964	0.158	1.076
Mississippi	0.211	0.921	0.164	1.038	0.123	0.967	0.143	1.087
Missouri	0.224	0.953	0.169	1.035	0.131	0.963	0.155	1.070
Montana	0.206	0.909	0.163	1.029	0.124	0.965	0.144	1.089
Nebraska	0.227	0.953	0.172	1.034	0.130	0.955	0.155	1.077
Nevada	0.225	0.907	0.183	1.010	0.120	0.974	0.140	1.077
New Hampshire	0.233	0.977	0.172	1.034	0.129	0.967	0.150	1.083
New Jersey	0.224	0.931	0.173	1.034	0.135	0.970	0.159	1.070
New Mexico	0.189	0.939	0.141	1.053	0.130	0.969	0.152	1.075
New York	0.228	0.946	0.174	1.030	0.138	0.967	0.163	1.065
North Carolina	0.224	0.960	0.167	1.040	0.132	0.961	0.157	1.073
North Dakota	0.213	0.932	0.164	1.035	0.128	0.961	0.151	1.080
Ohio	0.226	0.973	0.166	1.043	0.131	0.960	0.154	1.078
Oklahoma	0.188	0.910	0.144	1.051	0.128	0.969	0.150	1.079
Oregon	0.255	1.088	0.169	1.037	0.127	0.968	0.149	1.082
Pennsylvania	0.220	0.939	0.168	1.041	0.131	0.960	0.155	1.079
Rhode Island	0.227	0.937	0.175	1.031	0.129	0.961	0.151	1.085
South Carolina	0.226	0.957	0.170	1.034	0.126	0.967	0.147	1.080
South Dakota	0.232	0.989	0.170	1.028	0.129	0.951	0.156	1.064

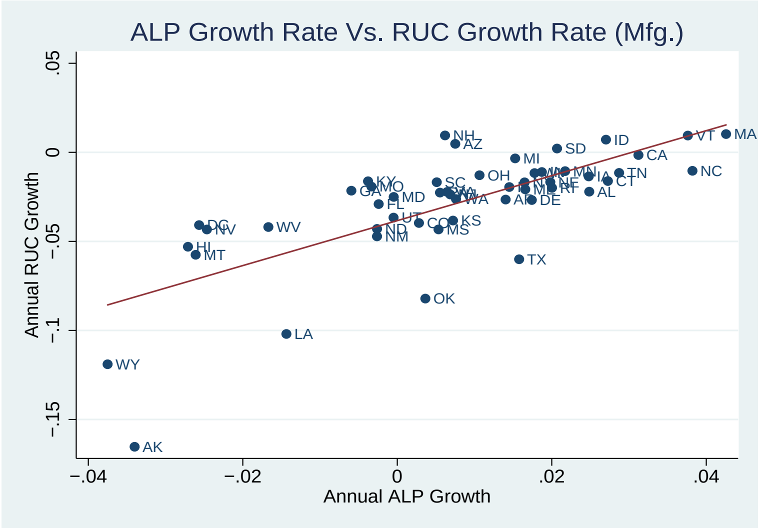
Table 3.10: **(Contd.)**

	Manufacturing				Services			
	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$	$Adj.RUC$	$\frac{P^I}{P^Y}$	$i+\delta-\pi$	$\frac{1-\tau z}{1-\tau}$
Tennessee	0.228	0.978	0.168	1.038	0.130	0.965	0.153	1.074
Texas	0.199	0.937	0.151	1.038	0.132	0.966	0.158	1.055
Utah	0.216	0.932	0.167	1.032	0.131	0.967	0.155	1.070
Vermont	0.238	1.005	0.171	1.036	0.127	0.969	0.146	1.093
Virginia	0.224	0.939	0.173	1.030	0.137	0.968	0.164	1.056
Washington	0.223	0.931	0.174	1.024	0.130	0.974	0.154	1.062
West Virginia	0.200	0.951	0.148	1.053	0.124	0.962	0.143	1.097
Wisconsin	0.227	0.974	0.167	1.042	0.128	0.963	0.149	1.085
Wyoming	0.165	0.932	0.122	1.054	0.118	0.965	0.138	1.083

For 1998-2007, we find a positive relationship between ALP growth and real user cost growth for both manufacturing and service sectors implying that states with a higher ALP growth associate themselves with a lower fall in the real user cost of capital, hence comparatively a larger role for MFP growth. We present this relationship in figure (3.11) panel (A) and (B) for the manufacturing and service sectors respectively. Even though we find a positive relationship between the two, the real user cost growth is negative for most of the states in both sectors due to short run shocks to the relative price ratio and financial component. This limits the MFP growth rates for all the states.

3.4.2.4 Real Wage Growth

US Manufacturing and Services: Table (3.11) presents the measures of ALP growth and real wage growth for both sectors. The manufacturing sector experiences a decline in the ALP growth to 1.52% which results from the price shocks originated in the mining and construction industries. Breaking the time period into two categories sheds further insight on this issue. During 2002-2007, the manufacturing sector experiences a near zero growth



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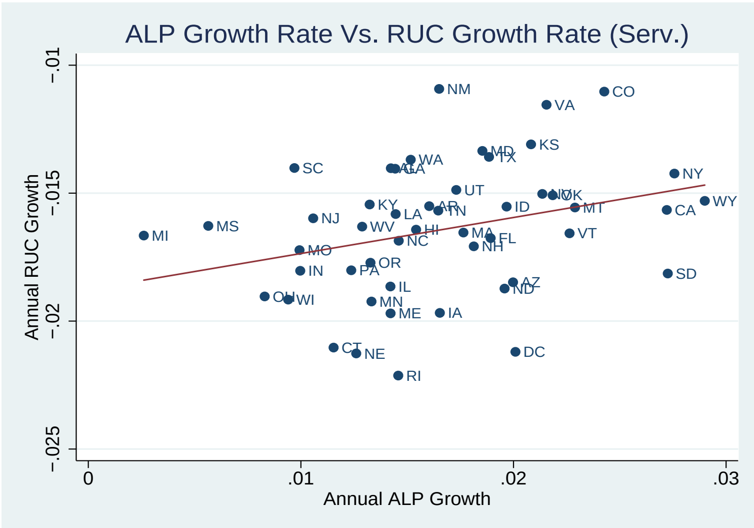


(B)

Figure 3.11: **ALP Growth Vs. Real User Cost Growth (1998-2007)**

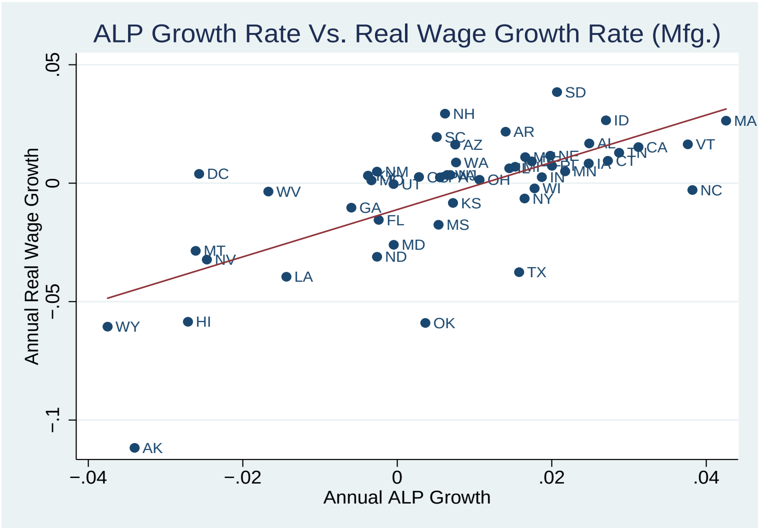
rate in ALP as the price shocks originate post 2002. The service sector experiences a steady growth rate of 1.77 % in ALP through out the period, but this growth rate is not as rapid as suggested by the literature. Jorgenson et.al. (2008) find the annual ALP growth for the private economy to be 3.09% for 2000-2005. Given the larger share of service sector in the private economy, one would expect a much higher growth rate for its ALP. Where as they find the growth rate of the hours worked to be -0.16% for the private economy, the persons engaged in production data from the BEA as a measure of labor force grows at the rate of 1.46% annually for the service sector during 1998-2007, especially due to post 2001 recovery of the labor market. This suppresses our measure of ALP growth as opposed to

Table 3.11: **Average Annual Real Wage Growth Rate (US) (1998-2007).** Note: ALPG=Average labor productivity growth rate for US, RWG=Real wage growth rate for US, St.Wt.= State weighted measures for US, CWG=Compensation per full time worker growth rate, RWG(CPI-U)=Real wage growth rate using Consumer Price Index-Urban, RWG(PCE)= Real wage growth rate using the deflator for Personal Consumption Expenditure (PCE). The presented numbers are in percentages.

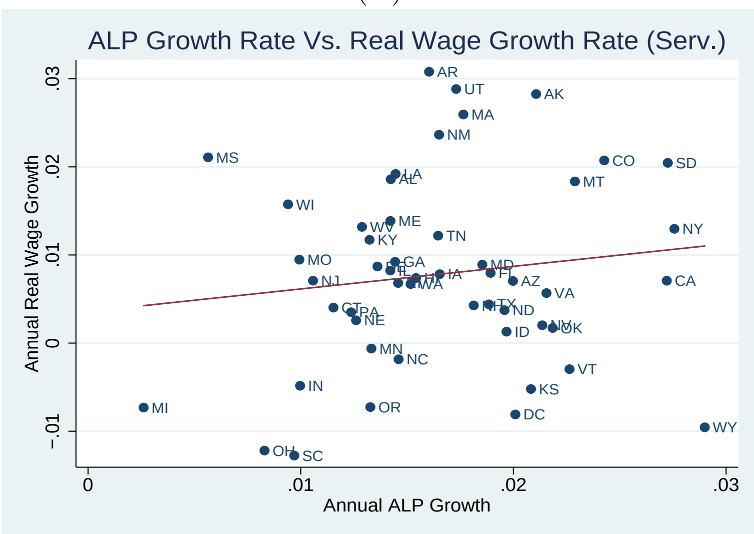
	1998-2007		1998-2002		2002-2007	
	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services
ALPG	1.23	1.78	3.23	1.76	-0.37	1.8
ALPG (St.Wt.)	1.52	1.77	3.33	1.75	0.07	1.79
RWG	-0.51	0.67	2.28	1.94	-2.74	-0.35
RWG (St.Wt.)	-0.001	0.69	2.28	1.97	-1.82	-0.32
CWG	0.83	1.65	4.03	1.76	-1.73	1.56
RWG (CPI-U)	0.11	0.19	0.36	1.52	-0.09	-0.88
RWG (PCE)	0.53	0.61	1.00	2.16	0.16	-0.63

that suggested by Jorgenson et.al. (2008). This rise in labor growth along with the moderate rise in the GDP deflator of the service sector causes the ALP growth rate to be much lower.

For 1998-2007, the real wage growth rates fall far behind the ALP growth rates for both the sectors, especially in manufacturing sector where the real wage growth rate is -0.001% per annum. The real wage growth rate for the service sector is 0.69% which lies far below the ALP growth rate of 1.77%. Although both sectors experience very high growth rates of real wage during the sub-period 1998-02, both sectors experience negative growth rates for the period 2002-07 due to sharp rise in the GDP deflators. Baker (2007) finds a sharp increase in the non-wage share of compensation during 2001-2006 and given the fact that the income variable in IPUMS-CPS data set refers to wage and salary income, the use of IPUMS-CPS data set can be another source for the low growth rates of real wage. As a robustness check, we compute the real wage growth using the “compensation per full time worker” data from the BEA for the US manufacturing and services. The use of “compensation per full time per worker” as the measure of real wage increases the real wage growth rates to 0.83% and 1.65% annually for the manufacturing and service sectors respectively which is substantially higher than the measures derived from IPUMS-CPS. Using these measures of real wage growth improve the MFP growth rates to -0.14% and 0.42% for the manufacturing and service sectors respectively which are much lower than the primal growth rates of 0.45% and 1.01%. Again, one can argue that this divergence roots from the sharply falling real user cost which is affected by price shocks and business cycle fluctuations. Even the "compensation per full time worker" displays a negative growth rate of -1.73% during 2002-2007 due to price shocks post 2002 in the manufacturing sector. For the service sector, it declines marginally due to the moderate rise in GDP deflator.



(A)



(B)

Figure 3.12: **ALP Growth Vs. Real Wage Growth (1998-2007)**

State Manufacturing and Services: Figure (3.12) (A) and (B) display the ALP growth against the real wage growth for the manufacturing and service sectors respectively. Even though we find a positive relationship between the two, around twenty states experience negative real wage growth and ALP growth as our results on real wage growth and ALP growth for the manufacturing sector are influenced by price shocks affecting the SGDP deflators. In case of the service sector, though a positive relationship is found between the two, this relationship is not strong enough. This can be attributed to the fact that the real wage calculated using the IPUMS-CPS data set is depicting very low growth rates due to the rise in the share of non-wage compensation (Baker, 2007). During this period, more than 30 states experience an ALP growth rate below the national growth rate and a real wage growth rate below 1%. The ALP growth rate also remains low due the surge in labor force in post recession labor market recovery.

We can sum up the discussions for NAICS by citing Hsieh (2002) who argues that in the presence of temporary shocks in short run, the long run equality between the real user cost and marginal product of capital will not hold which will lead to biased measure of dual MFP growth. The NAICS data set covering 1998-07 is a fairly short run and affected by 2001 recession and price shocks post 2002. This adversely affects the measures of real user cost growth and hence creates a wedge between the primal and dual measures of MFP growth.

3.5 Concluding Remarks

The traditional growth accounting exercise to gauge the importance of MFP growth in driving the sectoral growth across US States, has been hindered by the lack of availability of state specific capital stock data. In this paper, we employ a dual growth accounting technique to measure the MFP growth which relies on observed real factor price data. In the process, we construct a unique state level data set on the real user cost of capital for the manufacturing and service sectors paying particular attention to inter-state variations in the composition of output, relative prices of investment goods, effective corporate income taxes, and the inflation rates. While we find MFP growth to be the driving force behind the growth of manufacturing sector, the service sector attributes a minimal role to MFP growth and is driven by capital accumulation. The variations in MFP growth play a much larger role in explaining the variations in labor productivity growth in the manufacturing sector than in the service sector. Our findings suggest that the huge deviations of the dual measures from the primal ones root from inconsistencies between the observed real user cost and the implied real user cost of the BEA. While the real user cost for the manufacturing sector experiences a positive growth implying a high MFP growth, the service sector experiences a negative growth due to the rapid decline in the relative price ratio of investment goods due to "Investment Specific Technological Change (ISTC)". This implies a very high growth of capital accumulation and a very low growth of MFP in explaining the service sector growth. Our findings suggest that the average growth in real user cost of capital is non-zero and shows wide variability across states.

Chapter 4

Schooling and R&D Externalities: Evidence from A Dual Growth Accounting Application to US States

4.1 Introduction

The importance of schooling and research and development (R&D) in driving multi-factor productivity (MFP) growth has received substantial attention in the economic growth literature. Nelson and Phelps (1966) attribute a significant role to human capital in promoting technological diffusion through the adoption and the implementation of newly available technologies. Apart from adoption, human capital also stimulates technological improvement by generating innovations through R&D activity (Romer, 1990). A considerable amount of cross country studies has been centered around identifying such positive externalities from schooling and R&D efforts (Benhabib and Spiegel, 1994, Coe and Helpman, 1995 and Benhabib and Spiegel, 2005). Policy actions in promoting investments in human capital and R&D activity are often prescribed in the presence of such positive externalities. In a similar fashion, identifying these externalities in a regional set up has implications for regional policy making. It can be argued here that a state with higher level of education not only creates better ideas, but also is more favorable to adopt, implement and execute the newly available ideas and hence to absorb the knowledge spillovers. However, the literature has failed to provide evidence for such externalities from education at the regional level in US (Acemoglu and Angrist, 2001 and Ciccone and Peri, 2006). While the literature has focussed on identifying externalities from schooling, the studies to document R&D externalities are seldom found for US regions. Though investments in R&D stimulate innovations and contribute to technological improvement, in the absence of barriers to technological adoption, a new innovation in one state will immediately flow to other regions. Ex-ante, this weakens the link between R&D activity and productivity growth at the regional level. However, a case for R&D externalities can be made through an indirect channel where a state promoting R&D through higher R&D expenditure will attract more efficient firms and hence, will add to its productivity.[1] This chapter makes an important contribution to the existing literature by providing empirical evidence for average schooling and R&D externalities for the US states.

As a first step to achieve the objective of identifying schooling and R&D externalities, this chapter employs a dual growth accounting framework to construct the state-specific measures of MFP growth for the non-farm, non-mining private sector from 1980 onwards. The idea behind dual growth accounting is that any growth to MFP which causes output to grow would also cause the marginal product of the factors to grow (Hsieh, 1999, 2002). MFP growth can then be measured as a weighted average of the growth rates of the real factor prices, i.e. the real wage and the real user cost. Our results from the growth accounting exercise suggest that contrary to the primal measures derived from the BEA data set, the dual measures closely follow the pattern of the productivity slowdown. However, we fail to capture the pattern produced by the productivity revival due to short-run fluctuations in the real user cost of capital in post 2001 period. Restricting our analysis to 1980-2000, we establish that the source of divergence between the primal and dual measures originates from inconsistencies between the observed and the BEA implied real user cost of capital. While the BEA series experiences positive growth, our constructed series has negative growth due to a downward trending relative price ratio of the investment goods providing evidence for "Investment Specific Technological Change (ISTC)" and a moderately declining tax component. This has implications for the growth rate of the capital stock produced by BEA. The failure of primal measures to exhibit the pattern established by the existing literature cautions against apportioning the BEA capital stock data to the states in order

[1] Holmes (1998) provides positive evidence for the role played by probusiness state policies on the location of the manufacturing industries.

to carry out growth accounting exercises. Most importantly, our finding of wide dispersion in real user cost growth across states raises scepticism in approximating MFP growth only to real wage growth (Ciccone and Peri, 2006 and Iranzo and Peri, 2009).

In the second stage of the chapter, we utilize an empirical framework to explore the association between our constructed MFP growth and schooling and R&D expenditure. However, our empirical model fails to identify significant schooling and R&D externalities through the inclusion of the change in educational attainment and the growth of R&D expenditure as explanatory variables in the line of Ciccone and Peri (2006) and Iranzo and Peri (2009). This specification is equivalent to including these variables as inputs in the technological growth process. Nelson and Phelps (1966) caution against utilizing such an approach and instead argue that MFP growth of a country depends on its technological gap from the frontier technology. The speed at which this gap will be closed depends on the country's human capital level ensuring technological catch-up. Benhabib and Spiegel (1994, 2005) complement the Nelson and Phelps (1966) model by introducing an endogenous feature of technological growth in it where technological growth depends directly on the level of human capital and is enhanced through innovations resulting from it. However, the authors caution that it is difficult to identify positive externalities from human capital in the presence of catch-up effect. A similar case can also be made for the state R&D expenditure. Not only does a higher share of R&D expenditure improve technological growth by attracting more efficient firms to the state, a state with higher R&D share also takes better advantage of technological diffusion and hence closes the gap faster. In our OLS estimation, the coefficient of average years of schooling per worker turns significant only after controlling for the catch-up effect by introducing the log of initial labor productivity. Further, the empirical model uses a different specification to capture the endogenous technological progress and catch-up effect associated with schooling separately. The empirical findings lend support to the argument that schooling generates externalities by not only enhancing the technological improvement, but also by speeding up the technological diffusion, hence closing the productivity gap between the rich and the poor. Though the R&D share variable enters significantly in the model, the estimate for R&D externalities is low with a point estimate of 0.09. The strength of the coefficient does not improve much even after controlling for the catch-up effect. Further, separating the R&D externalities resulting from endogenous technological progress from that resulting from the catch-up effect reveals that R&D expenditure generates significant positive impact on productivity growth only through catch-up.

To address the endogeneity issues of schooling and R&D expenditure, we utilize instrumental variables to identify the exogenous determinants of the level of average schooling and R&D expenditure. Our schooling variable is instrumented using the young per adult ratio and the share of African American in the population of a state at the beginning year.[2] With the increasing educational attainment of the younger generation, states with higher young per adult ratios will experience higher schooling per worker compared to the states with lower ratios. With the African-American population experiencing substantial growth in educational attainment to match the rest of the population, a state with a higher share of African-Americans at the starting year gains substantially in schooling. We include the young per adult ratio in a quadratic specification and also include the interaction of young per adult ratio and share of African Americans as an additional instrument in the model. The R&D variable is instrumented using the number of research universities per thousands of population in each state. The number of research universities reasonably represent the state R&D expenditure with these universities drawing substantial R&D support from federal and non-federal sources. Similar to the OLS estimates, the schooling variable enters significantly only after controlling for the catch-up effect by introducing the log of initial labor productivity. Further, the empirical exercise successfully documents the importance of schooling in directly enhancing technological growth through the endogenous technological innovations and through the catch-up effect separately. The R&D coefficient increases twice in magnitude in comparison to the OLS estimates and enters significantly once we control for the catch-up effect. Further analysis fails to capture any externalities resulting from the innovations associated with R&D, rather concludes that R&D generates externalities only through catch-up.

The rest of the chapter is organized as follows: the next sub-section reviews the literature.

[2]Ciccone and Peri (2006) use similar instruments to instrument the change in years of schooling.

Section (4.2) briefly reviews the dual growth accounting procedure and discusses the results. Section (4.3) presents the empirical evidence and section (4.4) concludes.

4.1.1 Related Literature

In the absence of literature on R&D externalities at a regional level, this subsection only documents the available literature on externalities resulting from schooling. Conventionally, the literature utilizes a Mincerian wage equation to identify schooling externalities through the impact that average schooling has on the individual level real wage after controlling for individual characteristics. The idea behind this methodology is that workers will earn a higher real wage in a region with higher average schooling if aggregate schooling exerts a positive impact on aggregate productivity. As a starting point, Rauch (1993) documents a 2.8%-5% increase in MFP resulting from an additional year of schooling for the US cities. Acemoglu and Angrist (2001) warn that the positive association between wages and schooling might be overstated in the presence of an endogenous schooling variable. Endogeneity of the average schooling variable is plausible in the presence of selective migration of educated workers to the states experiencing higher wages. Similarly, an omitted variable might drive both wages and average schooling to overstate the evidence of schooling externalities. Utilizing the compulsory schooling laws to capture exogenous changes in average schooling, the authors fail to identify significant positive schooling externalities for the US states which is contradictory to the significant evidence obtained from their OLS estimates.[3]

Cicccone and Peri (2006) caution against using the Mincerian approach to capture schooling externalities and argue that this approach yields positive schooling externalities even when true externalities are absent as it overestimates the real wage growth. They propose to use a measure of real wage growth constructed by weighting the real wage growth rates of different educational categories by their income shares or its equivalent, growth in the average real wage constructed by keeping the employment share of different educational categories in the labor force fixed at the initial year. While the first measure of real wage growth is the

[3]Moretti (2004) provides evidence of significant positive externalities from college education for the US cities using the lagged demographic structure of the cities and the presence of land-grant colleges to instrument the changes in the share of college graduates.

dual measure in the absence of real user cost growth, the authors coin the second measure as a "constant-composition" approach. The authors fail to identify significant externalities resulting from average schooling for the US cities and states in a "constant-composition" approach where they utilize the demographic structure and the share of African Americans of the cities and the states at beginning of the study period to instrument the changes in schooling.[4] The method adopted by Cicccone and Peri (2006) and Iranzo and Peri (2009) is the closest to that followed in this chapter.

4.2 Dual Growth Accounting

Our analysis begins with the construction of MFP growth measures for the non-farm, non-mining private sector for all US states. To achieve this objective, we exploit the dual growth accounting procedure discussed in detail in chapter 3. This section briefly summarizes the dual accounting method and discusses the results for MFP growth.

The idea behind the dual growth accounting is that any growth to MFP that causes output to grow, will also cause the real factor prices, i.e. the real wage and the real user cost to grow (Jorgenson and Griliches, 1967, Hsieh, 1999,2002, and Aiyar and Daalgard, 2005). So, MFP growth measures can be constructed as an average of the growth rates of the real wage and the real user cost, weighted by the labor income share (α_L) and the capital income share ($\alpha_K = 1 - \alpha_L$) respectively.

$$MFPG_{s,t} = \bar{\alpha}_{K,s}\hat{r}_{s,t} + \bar{\alpha}_{L,s}\hat{w}_{s,t} \tag{4.1}$$

where $\bar{\alpha}_{L,s} = \frac{\alpha_{L,s,t}+\alpha_{L,s,t-1}}{2}$, $\bar{\alpha}_{K,s} = \frac{\alpha_{K,s,t}+\alpha_{K,s,t-1}}{2}$, $\hat{r}_{s,t}$ = real user cost growth rate and $\hat{w}_{s,t}$ = real wage growth rate. The labor income share (α_L) follows from the procedure by Gollin (2002), discussed in chapter 3.

Following the seminal works by Hall and Jorgenson (1967) and Coen (1968), the real

[4] Iranzo and Peri (2009) provide evidence of significant positive externalities from an increase in years of college education per worker, but fail to find the same with an increase in years of high school per worker as a measure of average schooling in a "constant-composition" approach.

user cost is constructed as

$$RUC_{s,t} = \frac{P^I_{s,t}}{P^Y_{s,t}}(i_t + \delta_{s,t} - \pi_{s,t})\frac{(1-\tau_{s,t}z_{s,t})}{(1-\tau_{s,t})} \tag{4.2}$$

We construct $P^I_{s,t}$ as a share weighted implicit price deflator using US sub-sectoral (industrial) investment price deflators. $P^Y_{s,t}$ is constructed by weighting the state-specific state GDP (SGDP) deflators of the sub-sectors. $\delta_{s,t}$ is a share-weighted real depreciation rate of the national sub-sectoral real depreciation rates. The assigned weights are the SGDP share of each industry (sub-sector) in total SGDP of the non-farm, non-mining private sector. i_t is the nominal interest rate, $\tau_{s,t}$ is the state specific effective corporate income tax rate which is constructed following Chirinko and Wilson (2008), $z_{s,t}$ is the present value of depreciation deductions of \$ 1 investment which is calculated using the double declining balance method by Hall and Jorgenson (1967) using state specific depreciation rates $\delta_{s,t}$. The inflation rate $\pi_{s,t}$ is constructed as a five year moving average lagged inflation of investment prices indices $P^I_{s,t}$ following Gilchrist and Zakrajšek (2007). The real user cost ($RUC_{s,t}$) is then adjusted based on the procedure discussed in equations (3.8) and (3.9) to obtain "$Adj\_RUC_{s,t}$ ($r_{s,t}$)" which is the real user cost for the rest of the analysis. The data sources for the construction of the real user cost are detailed in the data section of chapter (3) and the data appendix. We restrict our analysis here to avoid repetition.

Our constructed series on real wage growth is quality adjusted for four educational categories (some school, high school graduate, some college and college graduates) and gender following Hsieh (2002). This quality adjustment ensures that real wage growth results only from the growth of real wage of the labor groups and not due to the change in the composition of the labor groups which changes the average real wage, hence the real wage growth. The weighted real wage growth rate for state "s" is

$$\hat{w}_{s,t} = \sum_j \bar{S}_{L,j,s}\hat{w}_{j,s,t} \tag{4.3}$$

Here $\bar{S}_{L,j,s} = \frac{S_{L,j,s,t}+S_{L,j,s,t-1}}{2}$ where $S_{L,j,s}$ is the share of labor income of each group in total labor income, $j = education \times gender$ and "$\hat{w}_{j,s,t}$" refers to the log difference of the mean weekly real wage of group "j". Cicccone and Peri (2006) and Iranzo and Peri (2009) argue that MFP growth can be identified from the earning weighted real wage growth or its equivalent, growth in the average real wage constructed with skill composition (employment shares) fixed at the starting year. While we rely on the earlier method, they use the later method to construct the real wage growth. In contrast to ours, they base their real wage growth on four educational and eight experience groups for each state and the mean real weekly wage of each labor group corresponds to white, US born, married male workers. Our measure of real wage growth is based on the weekly wages derived from the micro data set of the March Current Population Survey (CPS) published at IPUMS-CPS for the period 1980-2008. The nominal wage is deflated using the implicit price deflator of SGDP. Our constructed wage growth and weeks worked corresponds only to full time equivalent employees. So, anybody working below 35 hours a week and 40 weeks per year is dropped from the sample.

We discuss the results for the MFP growth measures and its components below and contrast with the existing literature.

4.2.1 Discussion

4.2.1.1 Multi-Factor Productivity (MFP) Growth

Table (4.1) displays the results for MFP growth for the entire time period of 1980-2007. Column (1) presents the measures for the US non-farm, non-mining private sector obtained through weighting the state level measures. The labor productivity displays a growth rate of 1.92%. The real factor prices, i.e. the real wage and the real user cost grow at the rate of 1.14% and -0.62% respectively resulting in a MFP growth rate of 0.52%. The annual MFP growth rate of 0.52% contributes 27% to labor productivity growth. The growth rates presented in column (1) can be biased due to the weighting of the state level measures. As a robustness check, we construct direct measures for the growth rates of labor productivity, real wage, real user cost and MFP for the US. The results presented in column (2) match very closely to those reported in column (1). Further, using the data set from the BEA on persons engaged in production and capital stock, we carry out a primal exercise to construct MFP growth measures for the US. While the labor productivity growth from the primal exercise matches with ours, the MFP growth is nearly three times of our measure.

Table 4.1: **Average Annual MFP Growth Rate (1980-2007).** Note: The presented numbers are in percentages. ALPG=Average labor productivity growth rate, RWG=Real wage growth rate, RUCG=Real user cost growth rate, MFPG=Multi-factor productivity growth rate, Primal=Our primal measures of MFP growth rate calculated using the data from the BEA. Column "Compensation" refers to the MFP growth measures for the US using compensation per worker as wages.

	(1)	(2)	(3)	(4)
	St.Wt.	US	Compensation	Primal
ALPG	1.92	1.92	1.95	1.95
RWG	1.14	1.09	1.59	
RUCG	-0.62	-0.59	-0.59	
MFPG	0.52	0.49	0.82	1.46

Table 4.2: **Average Annual MFP Growth Rate (1980-1995, 1995-2007).** Note: The presented numbers are in percentages. ALPG=Average labor productivity growth rate, RWG=Real wage growth rate, RUCG=Real user cost growth rate, MFPG=Multi-factor productivity growth rate, Primal=Our primal measures of MFP growth rate calculated using the data from the BEA. Column "Compensation" refers to the MFP growth measures for the US using compensation per worker as wages.

	1980-1995				1995-2007			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	St.Wt.	US	Compensation	Primal	St.Wt.	US	Compensation	Primal
ALPG	1.76	1.74	1.78	1.78	2.12	2.14	2.16	2.16
RWG	0.99	0.89	1.24		1.33	1.33	2.02	
RUCG	-0.11	-0.10	-0.10		-1.25	-1.21	-1.21	
MFPG	0.60	0.55	0.79	1.49	0.41	0.43	0.87	1.42

The period of 1980-2007 demands further analysis given the fact that it incorporates two important periods for the US economy: the productivity slowdown (1973-1995) and the productivity revival (1995-2007). This also provides us an opportunity to contrast our results with the huge literature directed towards these two periods. Columns (1) through (4) and (5) through (6) in table (4.2) present the results for 1980-1995 and 1995-2007 respectively. Column (1) in table (2) depicts the state-weighted measures for 1980-1995. The labor productivity experiences a growth rate of 1.76%. MFP displays a growth rate of 0.60%, resulting from the growth rates of 0.99% and -0.11% for the real wage and the real user cost respectively. MFP growth contributes 34% to the labor productivity growth. The direct measure for the US in column (2) yields similar results. Fernald and Ramnath (2004) find the dual MFP growth to be 0.38% for the US non-farm business sector resulting from a real wage growth of 0.76% and a real user cost growth of -0.50% for 1973-1995. The marginal difference of our dual measures can be attributed to the differing study period. Further, the study by Jorgenson et.al. (2008) produces a growth rate of 0.39% for MFP using a primal growth accounting for the US private economy contributing only 26% to the labor productivity growth rate of 1.49%. Again, these growth rates for labor productivity and MFP are lower compared to ours as the time periods for both the studies do not coincide and secondly, while their study adjusts for quality to both labor and capital, our study only does the same for the real wage. Nevertheless, our results draw support from Fernald and Ramnath (2004) and Jorgenson et.al. (2008) in providing evidence for the productivity slowdown where the contribution of MFP growth to labor productivity growth is dismal. On the contrary, the primal measures derived from the BEA data set in column (4) report a growth rate of 1.49% for MFP contributing 84% to the labor productivity growth rate of 1.78% which fail to depict the pattern of productivity slowdown.

While our dual results are robust to the productivity slowdown literature, it fails to replicate the productivity revival. MFP experiences a dampened growth rate of 0.41% for 1995-2007 and contributes only 19% to the labor productivity which grows at 2.12%. This is contradictory to the findings of the existing literature. Jorgenson et.al. (2008) find the MFP growth to be 1% and 1.17% for the period 1995-2000 and 2000-2005 respectively which are substantially higher than those reported for 1973-1995 and its contributions to the labor productivity growth also increase to approximately 38%. Surprisingly, the primal exercise from the BEA data also fails to produce the desired pattern. The reported MFP growth rate in column (8) is 1.42%, marginally smaller than that of previous period and contributes only 66% to the labor productivity growth of 2.16% which is substantially smaller than the finding for 1980-1995. From the discussions above and the two subsequent sub-sections to be presented below, two inferences can be made : (1) contrary to the dual measures, the primal measures of MFP fail to exhibit the pattern established by the existing literature. The divergence between the primal and dual measures originates from inconsistencies between the observed real user cost and the implied real user cost from the BEA. This has implications for the growth rate of the physical capital stock of the BEA. With this backdrop, the reliability of the BEA capital stock data to carry out growth accounting exercise is questionable. So, the approximation of the BEA capital stock data to the states will not be appropriate to carry out state level exercise. Secondly, the dual measures are affected by short-fluctuations in the real user cost of capital post 2001 and fail to display the pattern of productivity revival. This calls for restricting the time period of our empirical exercise to 1980-2000. We present the MFP growth results for the US States for 1980-2000 below.

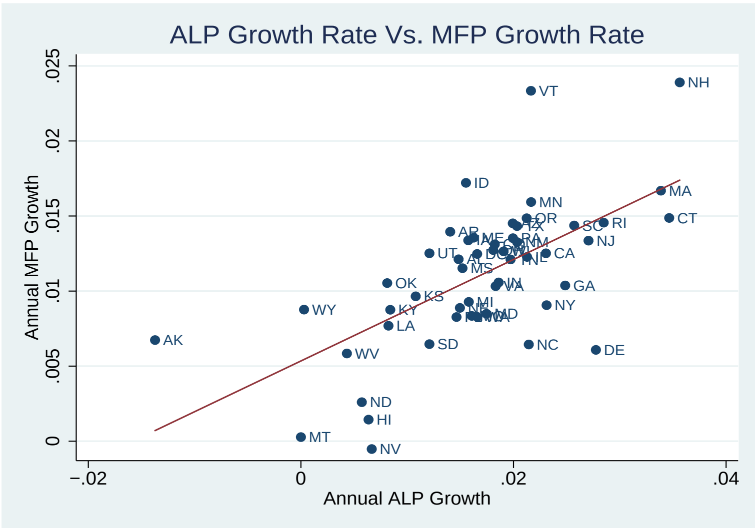


Figure 4.1: **ALP Growth Vs. MFP Growth**

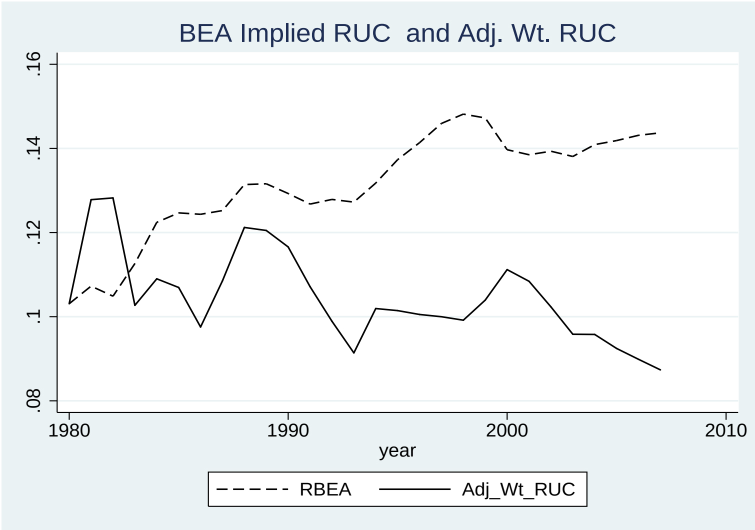
Figure (4.1) plots the annual labor productivity growth rate against the MFP growth rate for all the US states for the period 1980-2000. The existence of a positive relationship between the two is evident which substantiates the importance of MFP growth in driving labor productivity growth. The state weighted labor productivity and MFP growth for the US are 1.99% and 1.16% respectively for 1980-2000 where the contribution of MFP growth improves to 58% as post 1995 productivity growth revives. New Hampshire, Connecticut, Massachusetts, Rhode Island, New Jersey, South Carolina, New York and California are the states experiencing very high labor productivity growth rates between 2.3%-3.6%. While

New Hampshire experiences a very high MFP growth rate of 2.39% contributing 67% to its labor productivity growth, other mentioned states experience MFP growth rates between 1%-1.5% contributing 45% to their labor productivity growth on average. Vermont experiences a very high MFP growth resulting from very high factor price growth rates causing it to be higher than the labor productivity growth. On the lower side, Alaska is a clear outlier experiencing negative labor productivity growth. Montana, Wyoming, Nevada, Hawaii, North Dakota, West Virginia are states which experience near zero labor productivity growth, this causes the MFP growth to be equal to or higher than the labor productivity growth for smaller positive real factor price growth rates.

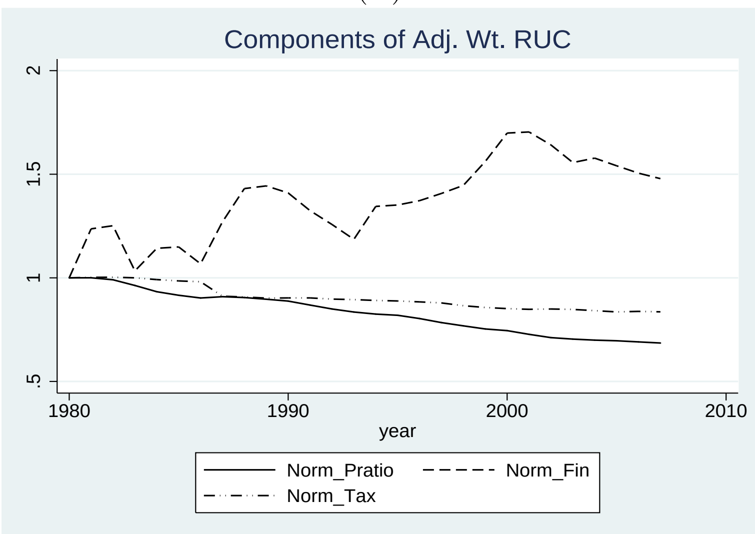
4.2.1.2 Real User Cost Growth

Figure (4.2) panel (A) plots our constructed real user cost of capital against the BEA implied real user cost. The divergence between the two series is clearly evident and highlights inconsistencies between the primal and dual measures of MFP growth. While the BEA series trends upward, our constructed series shows a downward trend. Panel (B) presents the components of the constructed real user cost normalized to their 1980 values. The financial component follows very closely to the movement of the BEA implied series. The divergence between the two series in panel (A) originates from the rapid decline in the relative price ratio and the modest decline in the tax component. However, it is worth noticing that post 2000 the similar pattern between the financial component and the BEA real user cost is no more evident. We discuss the time periods 1980-1995 and 1995-2007 separately below.

The divergence between the constructed real user cost and the BEA implied real user cost is evident for 1980-1995 from figure (4.2) panel (A). While the BEA series grows at a rate of 1.91% annually, our constructed series falls at the rate of 0.11%. One of the prime factors that generates very low growth in the constructed real user cost is the rapid fall in the relative price ratio of the investment goods which falls at the rate of 1.33% annually. Greenwood et.al. (1997) provide evidence for rapid accumulation of "Equipments" in response to the rapid fall in the relative price ratio resulting from the technological improvements in the "Equipment" producing industries. This phenomenon of "Investment Specific Technological



(A)



(B)

Figure 4.2: **BEA Implied User Cost and Adjusted Weighted Real User Cost**

Change" is captured through the rate of fall in the relative price ratio which is documented to be 3.21% by the authors for 1950-1990. The moderate rate of fall in our paper can be attributed to the fact that our price index for investment goods refers both to "Equipments and Softwares" and "Structures" in contrast to Greenwood et.al. (1997) and secondly, to the differing study period. The other factor which is also responsible in producing a declining trend, is the tax component which has a one time sharp drop in 1987 due to the cut in the federal corporate income tax rate to 34%.

For 1995-2007, while the BEA implied real user cost displays a growth rate of 0.38% contrasting the earlier period, our constructed series depicts an even lower growth rate of

-1.25%. The literature on US productivity growth attributes a greater role to IT capital accumulation and productivity growth in IT producing industries for the productivity surge during the period 1995-2000 and emphasizes the importance of non-IT sector for the post 2000 growth (Jorgenson et.al., 2008). Our study provides evidence for IT importance from a downward trending relative price ratio which falls at an even faster rate of 1.89% for 1995-2000 implying huge capital accumulation. Post 2000, an improvement to MFP of the non-IT sector would lead to a fall in the GDP deflator (P^Y), hence improving the growth pattern of the relative price ratio. We document similar evidence where the rate of fall of the relative price ratio improves to 1.20%. A further investigation concludes that the negative growth rate of -1.25% of our constructed series originates during 2000-2007 where the real user cost sharply falls at the rate of 3.45% due to the financial component which falls at the rate of 1.98%. This fall in the financial component is also compounded by the downward trending relative price ratio and tax component. The negative growth in the financial component results from a falling AAA corporate bond yield post 2001 recession. The BEA implied user cost which mimics the movement of the financial component very closely till 2000, post 2000 it diverges and grows at a rate of 0.4%. This provides evidence that our constructed series is adversely affected by the post 2001 interest rate movement and hence calls for restricting our exercise to 1980-2000.

Fernald and Ramnath (2004) argue that a growth to MFP increases the marginal product of capital and labor. A higher marginal product of capital leads to rapid accumulation of capital and hence causes the marginal product of capital to fall over time. But this capital accumulation will lead to a further increase in the marginal product of labor (real wage), hence a dual growth accounting approach would still capture the MFP growth despite the fall in the marginal product of capital. One can definitely furnish this argument to defend the downward trend in real real user cost. However, we do not see a substantial gain in the real wage growth in table (4.2) to generate a MFP growth rate documented by the productivity revival, hence we conclude that the real user cost is adversely affected by the short-run fluctuations in the interest rate post 2001, hence limiting our study period to 1980-2000.

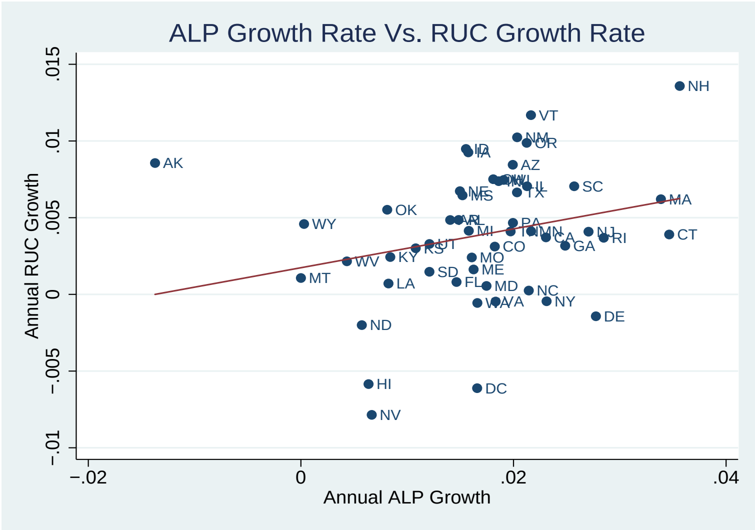


Figure 4.3: **ALP Growth Vs. Real User Cost Growth**

Figure (4.3) plots the annual labor productivity growth rate against the real user cost growth rate for all the US states for the period 1980-2000. Though the regression line establishes a positive relationship between the two, the relationship is not very strong. Here it would be useful to refer the reader to our discussion on real user cost growth and labor productivity growth for the manufacturing and service sectors for the US states in the previous chapter. During the productivity slowdown, manufacturing sector experienced a higher growth in MFP causing a higher growth in real user cost, hence displaying a positive association between labor productivity growth and real user cost growth. On the contrary, service sector was the worst affected and experienced a dampened MFP growth where the contribution of MFP growth to labor productivity growth was minimal. In fact for the period 1980-1997, we document a strong negative relationship between labor productivity growth and real user cost growth in the service sector providing evidence of a stronger role for capital accumulation in driving the labor productivity growth. With these two opposing patterns in the two sectors, the relationship between the real user cost growth and the labor productivity growth is not very robust in the non-farm, non-mining private sector. While New Hampshire, Vermont, New Mexico, Oregon, Idaho and Iowa experience very high growth rates (approximately 1%), Nevada, DC, Hawaii, North Dakota, Washington, New York, Virginia and Delaware associate with negative growth rates for real user cost.

One of the important conclusions from the above figure is the huge variation in the real user cost growth across states. This suggests that the approximation of MFP growth as in Ciccone and Peri (2006) and Iranzo and Peri (2009) to real wage growth is unwarranted and would lead to mismeasurement of MFP growth.

4.2.1.3 Real Wage Growth

The growth literature suggests that in the presence of a constant labor income share, the labor productivity and real wage should grow at the same rate. In US, there has been a concern that the real wage is not keeping up with the labor productivity growth. Column (1) of Table (4.1) clearly provides evidence for this where the real wage displays a growth rate of 1.14% for 1980-2007 falling behind the labor productivity growth rate of 1.92%. This phenomenon is also evident for the sub-periods 1980-1995 and 1995-2007 in columns (1) and (5) in Table (4.2).

Our measures of real wage growth are derived from the IPUMS-CPS data set. This data set is top-coded and allows us to adjust for "quality" based on education and gender. With these two factors, the constructed real wage growth can be a source of divergence between the primal and dual measures if this real wage growth differs from that derived from the BEA "Compensation" data. The measure of real wage growth based on the "Compensation per full time worker" from BEA is not top coded and does not undergo "quality adjustment", so the implied MFP growth using this data is directly comparable to the primal accounting results.[5] As a robustness check, Table (4.1) column (3) presents direct MFP growth measures for the US using the real wage growth measures derived from the "Compensation per full time worker". It can be clearly seen that the real wage growth increases to 1.59% compared to 1.14% of the IPUMS-CPS measure. Though the MFP growth rate increases to 0.82% for 1980-2007, it is still substantially behind the primal measure. This pattern is also observed in the two sub-periods. Columns (3) and (7) in table (4.2) present the real wage growth measures using the "Compensation" data for 1980-1995 and 1995-2007 periods respectively.

[5] The primal accounting exercise using the BEA data on persons engaged in production and capital stock does not undertake any quality adjustments based on the labor groups and type of capital goods.

For 1980-1995, the real wage growth rate increases to 1.24% increasing the MFP growth to 0.79% which is still nearly half of the primal measure and contributes only 44% to the labor productivity growth in contrast to 84% with the primal measure. In column (7) in table (4.2), the real wage growth increases to 2.02% increasing the MFP growth to 0.87% from 0.41% for the period 1995-2007. However, this 100% increase in MFP growth still fails to leap near the primal MFP growth. With this backdrop, one can draw the conclusion that the wedge between the primal and dual measures originates from the divergence between the observed and the implied series of the real user cost and not from the real wage growth measures. We present the evidence of real wage growth for the US states with the restricted time period of 1980-2000 next.

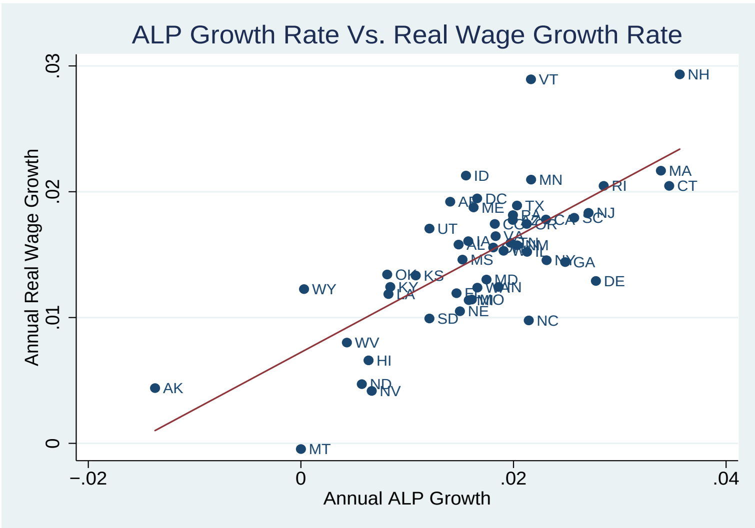


Figure 4.4: ALP Growth Vs. Real Wage Growth

Figure (4.4) plots the annual labor productivity growth against the annual real wage growth for all the US states for 1980-2000. A strong positive relationship between the two is evident. This is in accordance with the fact that the gain to productivity should be accrued to the worker in terms of higher real wage, hence a higher growth in labor productivity should associate with a higher growth in real wage. New Hampshire, Vermont, Massachusetts, Minnesota, Connecticut, Rhode Island associated with higher labor productivity growth experience real wage growth rates more than 2%. Montana, Nevada, Alaska and North Dakota represent the lower end of this relationship and display real wage growth rates around 0.5%.

One of the important inferences from the above discussion is that the divergence between the primal and dual measures originates from inconsistencies between the observed and the implied real user cost of capital. This has huge implications for the growth rate of the capital stock produced by the BEA. The failure of the primal measures from the BEA capital stock to exhibit the pattern established by the existing literature questions the approximation of the BEA capital stock data to the US states to carry out growth accounting exercise.

4.3 Empirical Analysis

4.3.1 Econometric Framework and Data

To capture the schooling and R&D externalities for the US states, we estimate the following regression equation

$$MFPG_s = \alpha_s + \beta_1 Schooling_s + \beta_2 R\&D_s + \beta_3 Controls + \epsilon_s \tag{4.4}$$

where $MFPG_s$ refers to the average annual growth rate of MFP in percentage for state "s". $Schooling_s$ and $R\&D_s$ refer to the measures of average schooling and R&D activity for state "s" respectively and ϵ_s represents the error term. Positive and significant β_1 and β_2 coefficients would provide evidence for schooling and R&D externalities. Regional dummies are introduced as additional control variables to capture the regional disparity in productivity growth. Additionally, we also include the log of initial labor productivity to control for "catch up" or "technological diffusion" in the spirit Nelson and Phelps (1966) and Benhabib and Spiegel (1994, 2005). Ideally, the regression equation should include the log of initial MFP, but in the absence of a measure, the log of initial labor productivity is a reasonable approximation.

The schooling variables are computed using the years of schooling per worker from the micro data set of the March Current Population Survey (CPS) published at IPUMS-CPS for 1980-2008. The data on schooling per worker is constructed using the years of schooling from the “HIGRADE” variable in the IPUMS-CPS data set which reports the highest grade completed for each worker in the sample for 1980-1991. Post 1991, the schooling attaintment is reported through a categorical variable “EDUC99”. The years of schooling for each worker is then calculated from the categorical variable using the conversion table in Park (1994). Since our measure for MFPG is derived for full time workers only, we restrict the sample to workers working for 35 hours a week and 40 weeks a year while constructing the schooling per worker for each state and each year. Our schooling variables are $\overline{Schooling}$ and $\Delta Schooling$, representing the average of schooling per worker for 1980-2000 and the average annual change in schooling per worker for 1980-2000 respectively for each state.

To construct the R&D variables, we utilize the data set on “National Patterns of R&D Resources” from the National Science Foundation (NSF) which reports R&D expenditures by state, performing sector, and sources of funds. This state level data set is available for every alternative year from 1987 and available annually from 1997. The computed R&D variables are $\overline{R\&Dshare}$ and $\Delta ln(R\&D)$. The first variable refers to the average of R&D expenditure as a share of state GDP for 1987-2000 and the second variable refers to the average annual growth rate in real R&D expenditure expressed in percentage. Though the data is available only through 1987-2000, we approximate the share and the growth rate of R&D expenditure to be the same for the entire time period of 1980-2000.

Table (4.3) presents the summary statistics for the major variables used in the empirical analysis. Two letter codes in the parenthesis represent the states with minimum and maximum values. Wide variation in the annual MFP growth is evident with New Hampshire exhibiting a very high MFP growth rate of 2.39% and Nevada experiencing a negative growth rate of -0.053%. The log of initial labor productivity ranges from the lowest value of 6.5 for New Hampshire to the highest value of 7.533 for Alaska. New Hampshire with a very low initial labor productivity leads the MFP growth distribution which is suggestive of poor states catching up with the rich states. The mean of average years of schooling per worker ($\overline{Schooling}$) is 13.103 years. DC and Arkansas represent the highest and the lowest end of this distribution respectively. Mean annual change in schooling per worker ($\Delta Schooling$) is 0.036 years with Rhode Island experiencing the highest gain in educational attainment per worker for 1980-2000. R&D expenditure shows wide variation across states in both cases when expressed as a share of GDP and as a growth rate.

Table 4.3: **Summary Statistics**

	Observations	Mean	Std. Dev.	Minimum	Maximum
MFPG	51	1.102	0.476	-0.053 (NV)	2.390 (NH)
$ln\frac{Y}{L}_{80}$	51	6.847	0.175	6.500 (NH)	7.533 (AK)
$\overline{Schooling}$	51	13.103	0.304	12.504 (AR)	13.888 (DC)
$\Delta Schooling$	51	0.036	0.018	-0.002 (AK)	0.064 (RI)
$\overline{R\&Dshare}$	51	2.127	1.600	0.288 (SD)	7.858 (NM)
$\Delta ln(R\&D)$	49	3.466	2.833	-4.298 (AL)	10.512 (NH)

Table 4.4: **Correlation Matrix**

	MFPG	$ln\frac{Y}{L}_{80}$	$\overline{Schooling}$	$\Delta Schooling$	$\overline{R\&Dshare}$	$\Delta ln(R\&D)$
MFPG	1.000					
$ln\frac{Y}{L}_{80}$	-0.587	1.000				
$\overline{Schooling}$	0.112	0.283	1.000			
$\Delta Schooling$	0.136	-0.407	-0.303	1.000		
$\overline{R\&Dshare}$	0.347	-0.085	0.370	0.002	1.000	
$\Delta ln(R\&D)$	0.172	-0.111	0.041	0.041	-0.109	1.000

Table (4.4) reports the correlation matrix for the major variables used in the empirical analysis. A strong negative correlation between MFP growth and log of the initial labor productivity symbolizes technological diffusion across states. The very low correlation between the schooling variables and the MFP growth draws support from the existing literature (Acemoglu and Angrist, 2001, Ciccone and Peri, 2006, and Iranzo and Peri, 2009) documenting a lack of average schooling externalities. R&D as a share of state GDP shows stronger positive correlation with MFP growth when compared to $\Delta ln(R\&D)$. A strong positive association between average schooling and R&D share signifies the importance of human capital to carry out R&D activity.

4.3.2 OLS Estimates

Since our measures of MFP growth are developed along similar lines to those of Ciccone and Peri (2006) and Iranzo and Peri (2009), we attempt to identify the schooling and R&D externalities using specifications similar to the reported studies by regressing MFP growth on the annual change in schooling per worker and the growth rate of real R&D expenditure.[6]

$$MFPG_s = \alpha_s + \beta_1 \Delta Schooling_s + \beta_2 \Delta ln(R\&D)_s + \beta_3 Controls + \epsilon_s \qquad (4.5)$$

Table (4.5) presents the OLS estimates for the regression equation (4.5). Column (1) reports the estimated coefficient for the basic model with change in years of schooling per worker as the only explanatory variable. The variable enters insignificantly in the regression model and the reported coefficient suggests that a one year increase in schooling per worker increases the MFP growth rate by 4.33 percentage points or alternatively, increases the MFP by 4.33%. Column (2) introduces three regional dummies as additional control variables with "North East" as the base region. All the regional dummies enter significantly in the equation providing evidence of regional disparity in MFP growth. The coefficient for the schooling variable changes its sign, but enters insignificantly. Column (3) drops the regional dummies and introduces the log of initial labor productivity as the control variable. The negative significant coefficient provides evidence for poor states catching up with the rich states. Convergence among the US states for GDP per capita and labor productivity is well acknowledged and has received substantial attention in the literature (Barro and Sala-i-Martin, 1991, 1992). Our finding complements the existing literature by providing similar evidence for MFP growth.

[6]Ciccone and Peri (2006) and Iranzo and Peri (2009) approximate the MFP growth to real wage growth and test the evidence of human capital externalities only.

Table 4.5: **OLS Estimates for Impact of Change in Average Schooling and R&D Expenditure on MFP Growth (1980-2000).** Note: Dependent variable is MFP growth in percentage for 1980-2000. Each column represents a separate regression. All regressions contain a constant term. Numbers in the parenthesis refer to the Heteroskedasticity robust standard errors. ***, **, * denote significance at 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Midwest		-0.565***		-0.502***	-0.493***		-0.527***		-0.467***	-0.475***
		(0.195)		(0.136)	(0.133)		(0.187)		(0.140)	(0.133)
South		-0.566***		-0.445***	-0.465***		-0.516***		-0.470***	-0.441***
		(0.177)		(0.097)	(0.090)		(0.173)		(0.106)	(0.089)
West		-0.645*		-0.536**	-0.516**		-0.643***		-0.346**	-0.558**
		(0.336)		(0.228)	(0.242)		(0.224)		(0.163)	(0.237)
$\Delta Schooling$	4.333	-0.119	-2.313	-5.403	-5.939					-7.043
	(4.309)	(6.142)	(3.635)	(4.506)	(5.150)					(5.085)
$ln\frac{Y}{L}_{80}$			-1.617***	-1.449***	-1.645***			-1.650***	-1.559***	-1.608***
			(0.478)	(0.382)	(0.411)			(0.494)	(0.450)	(0.399)
$\Delta ln(R\&D)$						0.029	0.022	0.018	0.005	0.014
						(0.028)	(0.025)	(0.021)	(0.018)	(0.018)
N	51	51	51	51	49	49	49	49	49	49
R^2	0.026	0.231	0.319	0.458	0.499	0.030	0.248	0.356	0.482	0.505
F	1.012	3.130	5.979	8.495	11.404	1.112	3.218	6.378	7.024	10.119

Column (4) includes all the additional control variables which enter significantly with the expected signs. However, the schooling variable fails to provide evidence of significant schooling externalities in both columns (3) and (4).[7] Our finding corroborates the earlier literature citing a lack of significant human capital externalities from average schooling (Ciccone and Peri, 2006).[8] Columns (6) through (9) repeat the exercise discussed above with the R&D variable. The R&D variable bears the expected positive sign, but fails to enter significantly in all the regressions.[9] Finally, column (10) includes both the schooling and R&D variables with all the controls, but we fail to document any evidence of significant schooling and R&D externalities.

The inclusion of change in educational attainment and growth of R&D expenditure into the growth regression is equivalent to including these variables as inputs in the technological growth process. Here, it would be apt to quote the conclusion of Nelson and Phelps (1966) who question this specification while substantiating the role of human capital in facilitating technological diffusion, "Our view suggests that the usual, straightforward insertion of some index of educational attainment in the production function may constitute a gross misspecification of the relation between education and dynamics of production (pp. 75)." The authors argue that in a technologically progressing economy, a better educated workforce acts as a catalyst in adapting and implementing newly available technology, hence speeding up the technological diffusion or catch-up. They develop a model where the productivity growth of a country depends on the technological gap of the country from the frontier technology level and a higher level of human capital ensures technological catch-up by filling this gap at a faster rate. Benhabib and Spiegel (1994, 2005) further develop this model by introducing endogenous productivity growth into it where productivity growth relies on the level of human capital and is directly enhanced through technological innovations resulting from it. Though the endogenous feature of the model suggests that a country with a higher level of human

[7] Due to lack of enough observation for R&D expenditure for DC and Delaware, the R&D growth for the mentioned states could not be calculated. To make the comparisons plausible, Column (5) reports the regression coefficient for the schooling variable with all the control variables after dropping DC and Delaware.

[8] Findings of Ciccone and Peri (2006) are based on their reported 2SLS results.

[9] Lack of significant R&D externalities may result as the data set on R&D expenditure only pertains to 1987-2000. However, similar regressions for the sub-period 1990-2000 do not yield significant positive R&D externalities.

capital will display a higher productivity growth, the authors caution that a technological backward country can display a higher productivity growth in the presence of this catch up effect. So, it will be difficult to identify the positive externalities resulting from human capital if the catch-up effect is not controlled for. This argument of technological diffusion can be aptly extended to the US states as a newly available innovation can easily be diffused across states in absence of barriers to flow of knowledge and a higher level of human capital will ensure a faster diffusion. A similar argument can be made for the state R&D activity. A state spending a higher fraction of its state GDP on R&D attracts more efficient firms ensuring higher productivity growth. However, in a similar fashion to human capital, it will be difficult to identify the externalities from R&D if the catch-up effect is not controlled for and further, it can be argued that the speed at which a state approaches the frontier state will depend on the state's promotion of R&D activity though its R&D expenditure. So, to capture schooling and R&D externalities, we use the following regression equation.

$$MFPG_s = \alpha_s + \beta_1 \overline{S}_s + \beta_2 \overline{RD}_s + \beta_3 \overline{S}_s * Catch-Up_s + \beta_4 \overline{RD}_s * Catch-Up_s + \beta_5 Controls + \epsilon_s \tag{4.6}$$

where S=Schooling and RD=R&D share. $Catch-Up = \frac{\frac{Y}{L}^{Max}_{80} - \frac{Y}{L}_{80,s}}{\frac{Y}{L}_{80,s}}$ represents the technological gap of a state from the frontier state in 1980. α_s captures the exogenous technological improvement. β_1 and β_2 coefficients capture the endogenous technological improvement associated with the level of schooling and R&D expenditure. β_3 and β_4 represent the coefficients for the catch-up effect.

Table (4.6) reports the OLS estimates for average level of schooling per worker and R&D share for 1980-2000. Column (1) presents the results for equation (4.6) which includes the schooling variable as the only independent variables. The regression coefficient fails to display statistically significant positive externalities for schooling. As discussed earlier, it is difficult to identify schooling externalities in the presence of the catch-up effect. In column (2), we introduce the log of initial labor productivity ($ln\frac{Y}{L}_{80}$) to control for this effect. With the introduction of $ln\frac{Y}{L}_{80}$, the schooling variable turns significant at the 1% level and bears the expected positive sign.

Table 4.6: **OLS Estimates for Impact of Average Schooling and R&D Share on MFP Growth (1980-2000).** Note: Dependent variable is MFP growth in percentage for 1980-2000. Each column represnts a separate regression. All regressions contain a constant term. Numbers in the parenthesis refer to the Heteroskedasticity robust standard errors. ***, **, * denote significance at 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\overline{Schooling}$	0.172	0.568***	0.497***	0.481**					0.309
	(0.184)	(0.167)	(0.146)	(0.187)					(0.231)
$ln\frac{Y}{L}_{80}$		-1.879***				-1.560***			
		(0.453)				(0.481)			
$\overline{Schooling}$*Catch-Up			0.081***	0.075***					0.073***
			(0.013)	(0.013)					(0.026)
Midwest				-0.354**				-0.368**	-0.326**
				(0.135)				(0.154)	(0.130)
South				-0.155				-0.318**	-0.176
				(0.119)				(0.147)	(0.124)
West				-0.240				-0.496**	-0.242
				(0.148)				(0.190)	(0.150)
$\overline{R\&Dshare}$					0.090**	0.098**	-0.163*	-0.133	0.068
					(0.036)	(0.039)	(0.095)	(0.082)	(0.118)
$\overline{R\&Dshare}$*Catch-Up							0.263**	0.220**	-0.008
							(0.105)	(0.086)	(0.111)
N	51	51	51	51	51	51	51	51	51
R^2	0.012	0.426	0.482	0.541	0.091	0.420	0.312	0.424	0.572
F	0.872	9.620	20.123	18.912	6.306	6.543	3.475	4.800	9.855

The schooling coefficient implies that a one year increase in schooling per worker increases the annual MFP growth by 0.57 percentage points or increases the MFP by an additional 0.57% annually. The significant negative coefficient for $ln\frac{Y}{L}_{80}$ provides strong evidence of poor states catching up with the rich states. Column (3) introduces schooling and its interaction with the "Catch-Up" variable as the independent variables in the model. This specification is the formal representation of the theory presented by Benhabib and Speigel (1994, 2005) to accommodate the endogenous technological progress associated with schooling along with the Nelson-Phelps catch-up effect. Both variables enter significantly at the 1% level with the expected positive signs. This lends support to the argument that schooling generates externalities by not only enhancing technological improvement, but also by speeding up the technological diffusion with a higher level of education closing the productivity gap between the rich and the poor faster. Column (4) introduces the regional dummies as additional control variables. Again, both variables enter significantly with positive signs in the regression and display similar strength as in column (3). Column (5) isolates the positive R&D externalities for the states through a statistically significant positive coefficient for the R&D share variable when introduced as the only explanatory variable in equation (4.6). This provides support to our argument that higher share of R&D expenditure ensures higher productivity growth by attracting more efficient firms. However, the coefficient of interest suggests a minimal 0.09 percentage point increase for MFP growth resulting from one percentage point increase in R&D share. This evidence is not as substantial as compared to schooling externalities. In column (6), we introduce $ln\frac{Y}{L}_{80}$ as an additional explanatory variable to control for any existing catch-up effect. One would expect a stronger positive association between R&D share and productivity growth once we control for catch-up, but the coefficient on the R&D variable experiences only a marginal increase of 0.008 percentage points. In column (7), we extend the Benhabib and Speigel (1994, 2005) specification to R&D by introducing R&D share and its interaction with the "Catch-Up" variable as the independent variables. R&D share displays a negative and significant coefficient which implies that R&D reduces technological improvement. However, this coefficient is significant only at the 9% level and with the introduction of regional dummies in column (8), this coefficient is not significant anymore. The "Catch-U" variable enter significantly in the model in both columns (7) and (8) with the expected positive signs. This attributes an important role to R&D in closing the technological gap between the rich and the poor states. Finally, column (9) includes both schooling and R&D variables together along with their interactions with the "Catch-Up" variable. The "Catch-Up" coefficient associated with schooling turns positive and significant. All other variables enter insignificantly in the model. This is plausible given the existing correlation between the R&D and schooling variables. So, we conduct a F test for their joint significance. Though we fail to reject the null hypotheses for the endogenous coefficients, we reject the null hypothesis for the "Catch-Up" variables at the 1% level. This further strengthens the evidence for schooling and R&D in closing the technological gap and hence, speeding up the catch-up process.

4.3.3 Instrumental Variable (IV) Estimates

The inferences drawn through OLS estimates will no longer be valid if the schooling and R&D variables are endogenous. The endogenous nature of schooling has received substantial attention in the literature (Bils and Klenow, 2000 and Acemoglu and Angrist, 2001). Bils and Klenow (2000) argue that the well acknowledged positive relationship between schooling and growth can be explained through the impact of growth on schooling rather than the other way round.[10] Similarly, a state experiencing a productivity surge might attract educated workers through selective migration causing the education level of that state to be higher (Acemoglu and Angrist, 2001), leading to reverse causality. A similar argument can be applied to R&D expenditure where states experiencing higher productivity growth attract higher R&D funding. So, in the presence of endogeneity, the OLS estimates will be inconsistent and will not provide a valid interpretation of the relationship. So, we rely upon the instrumental variable regression to address this issue.

Our variable of interest, schooling per worker, is instrumented using the demographic structure and the share of African-American in the population of the state following Ciccone

[10]Bils and Klenow (2000) also argue about the omitted variable bias where an omitted variable like enforcement of property rights induce both schooling and MFP growth.

and Peri (2006).[11] Our first instrument is young per adult ratio in 1980 (YPA80) which is calculated by dividing the population below the age of 18 by the number of adults in the population. The selection of this instrument relies on the trend of higher educational attainment of the younger generation compared to the older one. The marginal effect of YPA80 is increasing in YPA80 with a quadratic specification. Ciccone and Peri (2006) caution about the negative marginal effect for small values of YPA80 with a negative coefficient for YPA80 and a positive coefficient for YPA80*YPA80. In spite of that, the increasing marginal effect with YPA80 will still be indicative of the fact that the states with a higher young per adult ratio will be better off with higher schooling per worker compared to the states with lower ratios. With the African-American population experiencing substantial growth in educational attainment to match the rest of the population, a state with a higher share of African-Americans in 1980 (AA80) has substantial gains in schooling causing the schooling per worker to be higher for 1980-2000. Additionally, we also include the interaction of AA80 and YPA80 in the first stage regression for average schooling per worker. While we expect AA80 to enter with the positive sign, we expect AA80*YPA80 to bear a negative sign implying that a higher share of African-American in the younger generation will lead to a lower level of schooling per worker as the African-American population still lag behind the rest of the population in educational attainment. The other variable of interest, R&D share, is instrumented using the number of "Doctoral/Research Universities-Extensive" per thousands of population ($\frac{RU}{Population}$) in a state. With these universities drawing substantial support for R&D from federal and non-federal sources (Carnegie Foundation for the Advancement of Teaching, 2004), per capita research universities will reasonably represent state R&D expenditure. The data on "Doctoral/Research Universities-Extensive" is collected from "Carnegie Foundation for the Advancement of Teaching" for the available years of 1987, 1994 and 2000. The interactions of schooling and R&D with the "Catch-Up" variable are instrumented by interacting the respective instruments with "Catch-Up".

[11] Ciccone and Peri (2006) also use the share of workforce above the age of 50 as an instrument. We do not include this in our analysis as it did not enter significantly in any of the first stage regressions.

Table 4.7: **First Stage Regressions for $\overline{Schooling}$ & $\overline{R\&Dshare}$ (1980-2000).** Note: Columns (1) and (2) correspond to columns (1) and (2) in table (4.8) respectively. Columns (3) and (4) correspond to column (3) in table (4.8). Columns (5) and (6) correspond to column (4) in table (4.8). Columns (7) and (8) correspond to columns (5) and (6) in table (4.8) respectively. Columns (9) and (10) correspond to column (7) in table (4.8). Columns (11) and (12) correspond to column (8) in table (4.8). Columns (13) through (16) correspond to column (9) in table (4.8). Columns (1), (2), (3), (5) and (13) refer to the first stage regression for $\overline{Schooling}$. Columns (7), (8), (9), (11) and (14) refer to the first stage regression for $\overline{R\&Dshare}$. Columns (4), (6) and (15) refer to the first stage regression of $\overline{Schooling}$*Catch-Up. Columns (10), (12) and (16) refer to the first stage regression of $\overline{R\&Dshare}$*Catch-Up. Each column represents a separate regression. All regressions contain a constant term. Numbers in the parenthesis refer to the Heteroskedasticity robust standard errors. ***, **, * denote significance at 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AA80	0.054**	0.042**	0.080*	-0.003	0.057	-0.023							0.063	-0.319	-0.007	-0.330
	(0.020)	(0.020)	(0.047)	(0.044)	(0.044)	(0.042)							(0.055)	(0.505)	(0.053)	(0.407)
YPA80	-13.530*	-14.420**	-17.155**	-79.445***	-14.200*	-76.878***							-14.779**	37.697	-77.795***	51.016
	(6.981)	(6.949)	(7.039)	(7.910)	(7.212)	(7.791)							(7.070)	(64.581)	(7.102)	(77.913)
YPA80*YPA80	12.903**	13.757**	14.709*	80.532***	13.893*	79.869***							14.449**	-82.080	80.865***	-84.218
	(6.391)	(6.330)	(7.901)	(9.309)	(7.923)	(9.332)							(6.914)	(76.485)	(8.094)	(93.889)
YPA80*AA80	-0.133***	-0.109**	-0.160	0.028	-0.104	0.078							-0.114	1.079	0.046	1.115
	(0.046)	(0.045)	(0.116)	(0.106)	(0.108)	(0.102)							(0.112)	(1.085)	(0.109)	(0.888)
$ln\frac{Y}{L}_{80}$		0.422**						-0.329								
		(0.190)						(1.142)								
AA80*Catch-Up			-0.143***	-0.078	-0.074	-0.015							-0.080	0.635	-0.033	0.703
			(0.052)	(0.061)	(0.053)	(0.063)							(0.082)	(0.529)	(0.085)	(0.501)
YPA80*Catch-Up			-0.989	55.959 ***	0.059	56.838***							0.092	-35.381	56.953***	-21.625
			(4.496)	(4.113)	(3.832)	(3.725)							(3.689)	(30.280)	(3.584)	(27.600)
YPA80*YPA80*Catch-Up			1.647	-59.212***	-0.831	-61.334***							-0.823	79.108	-61.498***	55.862
			(9.972)	(8.868)	(8.374)	(8.026)							(8.165)	(66.669)	(7.868)	(60.399)
YPA80*AA80*Catch-Up			0.263**	0.106	0.133	-0.011							0.145	-1.611	0.022	-1.770
			(0.114)	(0.128)	(0.114)	(0.133)							(0.159)	(1.101)	(0.168)	(1.054)
$\frac{RU}{Population}$							656.077***	669.674***	264.376	-924.159***	405.045	-770.135**	-3.959	-1382.192	-30.706	-2045.342
							(174.054)	(186.440)	(260.377)	(324.777)	(304.129)	(380.581)	(210.594)	(1478.113)	(200.176)	(1336.938)
$\frac{RU}{Population}$*Catch-Up									815.936	2575.259***	552.521	2290.031**	-19.958	2159.815	-6.997	3150.986*
									(668.676)	(849.791)	(768.103)	(973.682)	(233.888)	(1463.176)	(257.022)	(1559.683)
Regional Dummies	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
F-test	11.958	14.200	141.993	6629.18	193.687	7312.34	14.208	12.902	13.222	4.592	11.371	2.885	157.027	13.448	5918.32	2.855
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)	(0.067)	(0.000)	(0.000)	(0.000)	(0.010)
N	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51

Table 4.8: **2SLS Estimates for impact of Average Schooling and R&D Share on MFP Growth (1980-2000).** Note: Dependent variable is MFP growth in percentage for 1980-2000. Each column represents a separate regression. All regressions contain a constant term. Numbers in the parenthesis refer to the Heteroskedasticity robust standard errors. ***, **, * denote significance at 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\overline{Schooling}$	0.137	0.544***	0.538***	0.602***					0.355
	(0.240)	(0.188)	(0.173)	(0.227)					(0.346)
$ln\frac{Y}{L}_{80}$		-1.864***				-1.605***			
		(0.455)				(0.561)			
$\overline{Schooling}$*Catch-Up			0.082***	0.079***					0.072**
			(0.012)	(0.014)					(0.028)
Midwest				-0.333***				-0.262	-0.295***
				(0.125)				(0.183)	(0.102)
South				-0.098				-0.212	-0.129
				(0.132)				(0.200)	(0.150)
West				-0.214				-0.459**	-0.229
				(0.142)				(0.226)	(0.140)
$\overline{R\&Dshare}$					0.107	0.208**	-0.013	-0.005	0.067
					(0.066)	(0.083)	(0.076)	(0.061)	(0.175)
$\overline{R\&Dshare}$*Catch-Up							0.252**	0.211**	0.012
							(0.106)	(0.104)	(0.152)
Overidentification (p-value)	0.33	0.64	0.46	0.16					0.30
N	51	51	51	51	51	51	51	51	51

The first stage regressions for regression equation (4.6) is reported in table (4.7). Columns (1) through (6) report the first stage results for schooling per worker and its interaction with "Catch-Up" for different specifications. While running the instrumental variable regressions, one of the first concerns is to check the relevance of the instruments used as the presence of weak instruments leads to imprecise estimation. Staiger and Stock (1997) argue that the test of joint significance of the instruments with a F statistic below 10 is indicative of weak instruments. The F values for the joint significance of the instruments are sufficiently higher than 10 in columns (1) through (6) in table (4.7) and this rejects the null hypothesis of joint insignificance. This lends support to our instrument selection. Columns (5) through (12) report the first stage results for R&D share and its interaction with "Catch-Up". The reported F statistics for instrument relevance is substantially higher than 10 in most of the cases which negates the case for weak instrument. Columns (13) through (16) report the first stage regressions for schooling per worker and R&D share when both variable are introduced together in the model with the full set of control variables. While the F values for joint significance is substantially higher than 10 for the schooling variables, it is less than 10 for the R&D variables. Though a case for weak instruments can be made with F statistics falling below 10, but we ignore this given that we successfully reject the null hypothesis of joint significance at the 1% level. Before proceeding to the 2SLS results, it is important to discuss the validity of the instruments which requires the included instruments to be uncorrelated with the error term (ϵ_s). However, the validity of the instruments can be tested only in case of over identified models. The p-values for the test of overidentification reported at the end of table (4.8) indicate that the null hypothesis of validity of instruments can not be rejected. The test statistic follows a chi-squared distribution with degrees of freedom equal to number of overidentifying restrictions.

Table (4.8) reports the 2SLS estimates for the impact of schooling and R&D share on MFP growth. Columns (1) through (4) and columns (5) through (8) represent the models with schooling and R&D share as the variables of interest respectively with the "Catch-Up" interactions. Column (9) reports the coefficients for the full model with both variables and additional controls. The 2SLS estimate for schooling fails to provide significant evidence of positive externalities when included in the regression model without controlling for the catch-up effect in column (1). Similar to the OLS estimates, the schooling coefficient enters significantly and displays evidence of positive externalities as soon as we control for the catch-up effect by introducing $ln\frac{Y}{L}_{80}$ in column (2). Columns (3) and (4) include schooling and its interaction with "Catch-Up" as the independent variables to formally represent the theory postulated by Benhabib and Speigel (1994, 2005). In both columns, schooling and its interaction with "Catch-Up" enter significantly with the expected positive signs. This further asserts that schooling not only directly stimulates technological innovation, but also plays an important role in closing the productivity gap between the poor and rich states. In comparison to the previously produced OLS estimates, columns (3) and (4) report marginally higher coefficients for schooling and its interactions. When the R&D variable enters exclusively in the model, the 2SLS estimate turns insignificant in column (5) which is contradictory to the significant R&D effect obtained from the OLS estimates. The R&D coefficient increases twice in magnitude and enters significantly at the 5% level with the introduction $ln\frac{Y}{L}_{80}$ in columns (6). Once we control for the catch-up effect, the relationship between R&D and MFP growth becomes more prominent. In columns (7) and (8), we introduce the R&D variable and its interaction with "Catch-Up". In both cases, while R&D share turns insignificant, its interaction with "Catch-Up" turns significant and bear the expected positive signs. This further substantiates our argument of the importance of R&D expenditure in speeding up technological diffusion. The coefficients are very similar to those obtained in OLS. Column (9) includes both variables with its interactions in the regression model. Similar to the OLS estimates, all the variables of interest fail to provide significant evidence of positive externalities except the "Catch-Up" variable for schooling. As argued earlier, this is plausible given the correlation between R&D and schooling. We conduct a test for joint significance of the variables to test this. While we fail to reject the null hypothesis for the endogenous components of technological growth resulting from schooling and R&D, we successfully reject the null for the joint significance of the "Catch-Up" coefficients at the 1% level . This attributes an important role to schooling and R&D expenditure in speeding up the technological diffusion, hence closing the productivity gap between the rich and the poor.

4.4 Concluding Remarks

Though there is significant evidence of schooling and R&D externalities in the cross-country studies, the regional evidences with respect to these are not robust. Identifying these externalities is of utmost importance in reference to regional policy formulation related to higher education and R&D activity. This paper contributes by constructing the MFP growth measures for the non-farm, non-mining private sector for all the US states in a dual growth accounting framework and by capturing the positive impact of schooling and R&D expenditure on the MFP growth. The empirical exercise concludes that positive significant externalities can only be observed after controlling for the productivity gap between the rich and the poor states. This substantiates the technology diffusion hypothesis of Nelson and Phelps (1966) which states that MFP growth depends on the gap of the country's technology level from the frontier technology. The speed at which this gap will be closed depends on the country's human capital level. We extend the same argument to R&D activity and our empirical exercise documents increased positive externalities from R&D activity once we control for catch-up. The instrumental variable regressions further substantiate the robustness of our findings.

Chapter 5

Conclusion

The research related to productivity growth measures at the regional level has been limited by the lack of data on the physical capital stock. The regional literature either assumes MFP growth to be similar across states or apportions the industry specific Bureau of Economic Analysis (BEA) physical capital stock data to the states based on the income share of each state to conduct the growth accounting exercise. While the first assumption is clearly unwarranted in the presence of a varying inter-industry composition across states, the second method has its own limitations due to the presence of measurement errors in the national physical capital stock.

To avoid such problems, this dissertation makes an important contribution to the regional studies by constructing sectoral multi-factor productivity (MFP) growth measures for all the US states. This is achieved by employing the alternative dual accounting framework which relies on observable real factor price data. In the process, the dissertation contributes by creating a unique state level data set on the real user cost of capital paying particular attention to inter-state variations in the composition of output, relative prices of investment goods, effective corporate income taxes, and inflation rates.

The sectoral level analysis gives us an advantage to validate our results given the huge literature developed surrounding the productivity slowdown where the manufacturing and the services displayed different productivity growth patterns. Our growth accounting exercise finds MFP growth to be the driving force behind the growth of the manufacturing sector and finds the service sector to be driven by capital accumulation instead. We find the results to be in accordance with the existing literature. A comparison with the primal measures obtained from the BEA data set suggests huge difference among both the measures which originates from inconsistencies between the observed real user cost and the implied real user cost of the BEA, especially for the service sector. Contrary to the BEA implied series, our constructed series for the service sector exhibits negative growth resulting from a rapidly falling relative price ratio of investment goods in evidence of "Investment Specific Technological Change (ISTC)". This implies a very high growth of capital accumulation as opposed to that suggested by BEA. This provides evidence for the presence of measurement errors in the national capital stock and cautions against apportioning the national data to the states for the growth accounting purposes. Further, this evidence establishes the methodological supremacy of the dual growth accounting method as it succeeds in displaying the pattern established by the existing literature. The study also finds the the average growth in the real user cost of capital to be non-zero and to display wide variability across states. This is an important finding given that some of the regional studies approximate the MFP growth by real wage growth.

The later part of the dissertation extends the accounting exercise to the non-farm, non-mining private sector and explores the impact of average education and R&D expenditure on productivity growth. While the previous literature has documented limited evidence of a positive association between the productivity growth and average education, there are not many studies at the regional level pertaining to the relationship between R&D and productivity growth. The existence of a positive association between productivity growth and average education and R&D is particularly important in shaping state policies related to education and R&D expenditure. The study finds that average schooling and R&D are associated strongly with productivity growth once we control for the catch-up effect in the spirit of Nelson and Phelps (1966) and Benhabib and Spiegel (1994, 2005). This attributes an important role to education and R&D expenditure in closing the gap between the rich and the poor states. This finding has clear implications in shaping state policies in promoting education and R&D.

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Appendix: Data

This section documents the data sources and the construction of the variables used in the dissertation. The dissertation uses the data on manufacturing sector, service sector and non-farm non-mining private sector for all the US states for 1980-1997 in Standard Industrial Classification (SIC) and for 1998-2007 in North American Industry Classification System (NAICS). Our major data source is Bureau of Economic Analysis (BEA) unless stated otherwise. In SIC, the data is collected in eight major industrial divisions, namely: Mining, Construction, Manufacturing, Transportation, Communication and Public Utilities, Wholesale Trade, Retail Trade, Finance, Insurance and Real Estate and Services. In NAICS, the data is collected in eighteen two digit industrial codes, namely: Mining, Utilities, Construction, Manufacturing, Wholesale Trade, Retail Trade, Transportation and Warehousing, Information, Finance and Insurance, Real Estate and Rental and Leasing, Professional, Scientific and Technical Services, Management of Companies and Enterprises, Administrative and Waste Services, Educational Services, Health Care and Social Assistance, Arts, Entertainment and Recreation, Accommodation and Food Services and Other Services. The manufacturing sector includes mining, construction and manufacturing industries and all other industries constitute the service sector. All the industries together except mining constitute the non-farm, non-mining, private sector.[1] The nominal series are converted to real series using the price indices with base year 2000.

[1] For convenience, we index the state level component with subscript "s", the three major sectors: manufacturing, services, non-farm non-mining private are indexed by subscript "i", and the major industries are indexed by subscript "j".

A1. Labor Share

A1.1 Gross Domestic Product by State (SGDP)

BEA publishes data on SGDP for each state industry-wise in its Regional Economic Accounts section. The data can be found at "`http://www.bea.gov/regional/gsp/`". The SGDP for any industry in any state is the value added in the production process in that industry. SGDP includes three components: compensation of employees, taxes on production and imports less subsidies and gross operating surplus.

A1.2 Compensation of Employees (CE)

The BEA regional economic accounts produced estimates on compensation of employees includes wages and salaries of employees and supplements to wages and salaries for each state industry wise. Wages and salaries are measured on "when earned" basis. The CE data for 1963-1997 and 2001-2007 can be found at "`http://www.bea.gov/regional/gsp/`" and for 1998-2001, the data can be found at state annual personal income section table number SA06 at "`http://www.bea.gov/regional/spi/`".

A1.3 Taxes on Production and Imports less Subsidies (ITS)

ITS includes both taxes on production and imports, and subsidies. Taxes on production and imports for a state includes taxes on production and imports at federal, state and local level. State and local level taxes includes non-personal property taxes, licenses and sales taxes and federal taxes include excise taxes on goods and services. Subsidies include subsidies given by the government to private business or other government agencies. The data is available at "`http://www.bea.gov/regional/gsp/`". The ITS data is not available from 1997-2000.

A1.4 Full-time Equivalent Wage and Salary Employment (FTE_WE)

The BEA published data on wage and salary employment is the average annual number of jobs in each area by "place of work". This series includes both full time and part time wage and salary employees with equal weight. State Annual Personal Income Table number

SA 27 provides the data on wage and salary employment (http://bea.gov/regional/spi/default.cfm?selTable=SA27).

But for our purposes, we need data on full time equivalent wage and salary employment. Though BEA does not provide this data at state level, but it furnishes data on Full Time Part Time Employees (FTPTE) and Full Time Equivalent Employees (FTEE) industry-wise for US at "http://bea.gov/industry/gdpbyind_data.htm". So, we apply an adjustment to the state level data which assumes that the FTEE and FTPTE ratio for each state is equal to its national ratio for each industry every year. This can be rephrased as the conversion rate of FTPTE to FTEE in an industry is same for all the states for that industry. The equation given below yields us full time equivalent wage and salary employment (FTE_WE) for each industry at the state level.

$$\frac{FTEE_{j,t}}{FTPTE_{j,t}} = \frac{FTE\_WE_{j,s,t}}{FTPT\_WE_{j,s,t}} \Longrightarrow FTE\_WE_{j,s,t} = \frac{FTEE_{j,t}}{FTPTE_{j,t}} FTPT\_WE_{j,s,t}$$

A1.5 Adjusted Total Employment (Adj_TE)

The total employment data provided by BEA includes full time and part time wage and salary employment which is by "place of work" and proprietors employment which is nearly by "place of residence". The industry wise data for each state is available at "http://bea.gov/regional/spi/default.cfm?selTable=SA25". For the proprietors employment, the data on non-farm sole proprietorship is collected through Internal Revenue Service tax data which is by "place of residence" but the non-farm partnership data may be by "place of residence" or "place of work". So, the series on total employment is by "place of work" with little error as defined by BEA.

Industry Economic Accounts of BEA provides industry-wise data on Persons Engaged in Production (PEP) and Full Time Equivalent Employees (FTEE) for US at "http://bea.gov/industry/gdpbyind_data.htm". The industry-wise data on self employed is backed out using PEP and FTEE. Similarly, we back out the proprietors employment (PE) by deducting the wage and salary employment from the total employment for each industry and each state. Ironically, the sum of proprietors employment over all the state for each industry is hugely different from the self employment (SE) data reported at the industry level for US. So for congruence, we adjust the proprietors employment (PE) data, using the following formula:

$$\frac{SE_{j,t}}{\sum_s PE_{j,s,t}} = \frac{adj\_PE_{j,s,t}}{PE_{j,s,t}} \Longrightarrow adj\_PE_{j,s,t} = \frac{SE_{j,t}}{\sum_s PE_{j,s,t}} PE_{j,s,t}$$

So, for our purpose, total adjusted employment is full time equivalent wage and salary employment (FTE_WE) and adjusted proprietors employment ($adj\_PE_{j,s,t}$) which is the state level equivalence of persons engaged in production (total labor). *Here it should be noted that the data on ITS is not available from 1998-2000 in NAICS. So, we impute the labor share of sector "i" and state "s" for 1998-2000 as the average labor share for the period 2001-2007 for the same sector and state.*

A2. Real User Cost of Capital

A2.1 Nominal Interest Rate (i)

We use Moody's Seasoned AAA Corporate Bond Yield for our analysis which is available at monthly frequency at Federal Reserve Bank, St. Louis web site. For any year, the nominal interest rate is the twelve-month average of this yield.

A2.2 Depreciation Rate (δ)

The depreciation rate for industry "j" is

$$\delta_{j,i,t} = \frac{D_{j,i,t}}{K_{j,i,t-1}}$$

where $D_{j,i,t}$ is real depreciation cost at time (t) and $K_{j,i,t-1}$ is real stock of capital at time (t-1). $D_{j,i,t}$ is calculated using the "Current Cost Depreciation of Fixed Assets" and "Chain-type Quantity Index for Depreciation". $K_{j,i,t-1}$ is calculated using the "Current Cost Net Stock of Fixed Assets" and "Chain-type Quantity Index for Net Stock Fixed Assets". BEA publishes data on private fixed assets by industry at annual frequency from 1947-2001 in

SIC classification and 1947-2007 in NAICS classification. The standard fixed assets tables in SIC and NAICS can be found at "`http://www.bea.gov/bea/dn/FAweb/Index2002.htm`" and "`http://bea.gov/national/FA2004/SelectTable.asp\#S3`" respectively.

To derive the sector and state specific depreciation rate $\delta_{i,s,t}$, we weight these depreciation rates with the industrial share of SGDP in each sector for any state. So, $\delta_{i,s,t}$ can be represented as

$$\delta_{i,s,t} = \sum_j \frac{P^Y_{j,i,s,t} Y_{j,i,s,t}}{P^Y_{i,s,t} Y_{i,s,t}} \delta_{j,i,t}$$

Similarly, US sectoral depreciation rates are constructed weighting the industrial depreciation rates by their industrial share of GDP in each sector.

A2.3 Present Value of Depreciation Allowance (z)

To calculate the present value of depreciation deductions, we follow the double declining balance method proposed by Hall and Jorgenson (1967). To use this method, we assume that the life time of capital (assets) for tax purposes is $t_{i,s,t} = \frac{1}{\delta_{i,s,t}}$. Given this, the present value of depreciation deductions can be calculated as

$$z_{i,s,t} = \frac{\frac{2}{t_{i,s,t}}}{i + \frac{2}{t_{i,s,t}}}[1 - e^{-(i+\frac{2}{t_{i,s,t}})t^+_{i,s,t}}] + \frac{1 - e^{-(\frac{2}{t_{i,s,t}})t^+_{i,s,t}}}{i(t_{i,s,t} - t^+_{i,s,t})}(e^{-it^+_{i,s,t}} - e^{-it_{i,s,t}})$$

Following Gilchrist and Zakrajsek (2007), we set the nominal interest rate, i to be 7%. The optimal switch over point $t^+_{i,s,t}$ which maximizes this depreciation deduction is $\frac{t_{i,s,t}}{2}$. The present value of depreciation deductions for the major sectors of US are calculated using the analogous to the previous equation with US counterpart.

A2.4 Investment Price Deflator (P^I)

We use the data on "Investment in Private Fixed Assets" and its "Chain type Quantity Index" from standard fixed assets tables of BEA to construct $P^I_{j,i,t}$ in SIC and NAICS. The base year for this series is 2000. To construct the sector and state specific investment price deflator $P^I_{i,s,t}$, we weight the industry level price deflator with the industrial share of SGDP in each sector for any state. So, $P^I_{i,s,t}$ can be represented as

$$P^I_{i,s,t} = \sum_j \frac{P^Y_{j,i,s,t} Y_{j,i,s,t}}{P^Y_{i,s,t} Y_{i,s,t}} P^I_{j,i,t}$$

Similarly, US sectoral investment price deflators are constructed weighting the industrial investment price deflators by their industrial share of GDP in each sector.

A2.5 Inflation Rate (π)

Following Gilchrist and Zakrajsek (2007), our constructed inflation rate is a five year moving average lagged inflation rate of the investment price deflator. So, we can write the inflation rate as

$$\pi_{i,s,t} = \frac{1}{5} \sum_{k=1}^{5} ln(\frac{P^I_{i,s,t-k-1}}{P^I_{i,s,t-k-2}})$$

The above described inflation rate is only applicable to SIC classification as it has a longer series of SGDP which enables us to construct a longer series of investment price deflator. Since the industry-wise data on SGDP in NAICS classification starts only from 1997, this method is not feasible.[2] We construct five year moving average lagged inflation rate of the industrial investment price deflator.

$$\pi_{j,i,t} = \frac{1}{5} \sum_{k=1}^{5} ln(\frac{P^I_{j,i,t-k-1}}{P^I_{j,i,t-k-2}})$$

We weight the above industrial inflation rate with the industrial share of SGDP in the sector "i" of each state to construct the sector specific inflation rate in NAICS.

$$\pi_{i,s,t} = \sum_j \frac{P^Y_{j,i,s,t} Y_{j,i,s,t}}{P^Y_{i,s,t} Y_{i,s,t}} \pi_{j,i,t}$$

The inflation rates for the major sectors of US are calculated using the analogous to the previous equations with US counterpart in SIC and NAICS classifications respectively.

[2]For the non-farm, non-mining private sector, we club both the SIC and NAICS investment deflators to create a longer time series for the investment price deflator.

A2.6 Corporate Income Tax Rate (τ)

We follow Chirinko and Wilson (2008) to construct the state specific effective corporate income tax rate. Since some states give tax deductions for the corporate taxes paid to the federal government while filing the state corporate income taxes, the legislated state corporate income tax rate would be different from the effective corporate income tax rate. The state effective tax rate can be written as

$$\tau_{s,t}^{ES} = \tau_{s,t}^{LS}(1 - d_{s,t}\tau_{s,t}^{EF})$$

Similarly people get tax deductions against the corporate taxes paid to the state government while paying federal corporate income taxes. So, the effective federal tax rate for the state would be different from the legislated federal corporate tax rate.

$$\tau_{s,t}^{EF} = \tau_{s,t}^{LF}(1 - \tau_{s,t}^{ES})$$

where E=effective, L=legislated, S=state, F=federal and d= tax deductibility

Given these two equations, the effective tax rates $\tau_{s,t}^{ES}$ and $\tau_{s,t}^{EF}$ can be solved as

$$\tau_{s,t}^{ES} = \frac{\tau_{s,t}^{LS}(1 - d_{s,t}\tau_{s,t}^{LF})}{1 - d_{s,t}\tau_{s,t}^{LS}\tau_{s,t}^{LF}}$$

$$\tau_{s,t}^{EF} = \frac{\tau_{s,t}^{LF}(1 - \tau_{s,t}^{LS})}{1 - d_{s,t}\tau_{s,t}^{LS}\tau_{s,t}^{LF}}$$

$$\tau_{s,t} = \tau_{s,t}^{EF} + \tau_{s,t}^{ES}$$

$\tau_{s,t}$ is the effective corporate income tax rate for the state. We obtain $\tau_{s,t}^{LF}$ from the Tax Foundation.[3] The data on $\tau_{s,t}^{LS}$ and $d_{s,t}$ are obtained from various editions of the "Book of the States" published by the Council of the State Governments. Till 2001, the "Book of the States" publishes data on corporate income tax rates as of January 1st every alternative years. So, we assume that if the data published is for January 1 ,1985, the corporate tax rate

[3] http://www.taxfoundation.org/taxdata/show/2140.html

is applicable for year 1984 and 1985. But post 2001, it has come up with yearly publications of state level corporate income tax rates as of January 1st. We assume that if the data published is for January 1 ,2002, the corporate tax rate is applicable for year 2002. The national level effective tax rate is obtained by weighting each state's effective corporate tax rate by its GDP share in national GDP.

A2.7 SGDP Deflator (P^Y)

We use the BEA regional economic accounts published data on SGDP, real SGDP (RSGDP) and quantity indices for 1980-97 to construct the SGDP deflators.[4] Given the quantity indices, we can derive implicit price deflator from 1980-1997 but for this we need SGDP of the base year 2000 for which data is not available in SIC. We find out the SGDP for 2000 in SIC using the following: for any year RSGDP is

$$RSGDP_{j,s,t} = \frac{QI_{j,s,t}}{100} SGDP_{2000} \Rightarrow SGDP_{2000} = RSGDP_{j,s,t} \frac{100}{QI_{j,s,t}}$$

After finding $SGDP_{2000}$, we calculate RSGDP for 1980-1997 using the quantity indices and using RSGDP and SGDP, we construct the state specific implicit price deflators for SIC industries ($P^Y_{j,s,t}$) for 1980-1997. We use the industry-wise SGDP and RSGDP in NAICS to back out the state specific implicit price deflators for each industry. These state and industry specific SGDP deflator are weighted by their respective industrial SGDP share to obtain the sectoral SGDP deflators.

In the similar fashion, we construct the industrial implicit price deflators for GDP ($P^Y_{j,i,t}$) for US. The sectoral deflators are constructed by applying the appropriate industrial GDP shares.

A2.8 Price of Capital (P^K)

The implicit price index for existing capital stock ($P^K_{j,i,t}$) is constructed using the "Current Cost Net Stock of Fixed Assets" and "Chain-type Quantity Index for Net Stock Fixed

[4]While the data for SGDP and quantity indices are available for the entire period, the data on RSGDP only available from 1990.

Assets". The state and sector specific price of capital is calculated using the appropriate SGDP shares as given below:

$$P^K_{i,s,t} = \sum_j \frac{P^Y_{j,i,s,t} Y_{j,i,s,t}}{P^Y_{i,s,t} Y_{i,s,t}} P^K_{j,i,t}$$

Similarly US sectoral price of capital is derived weighting the industrial price of capital with their respective GDP shares.

A3. Current Population Survey Data

To calculate the data on wages and weeks worked, we use the data on the March Current Population Survey (CPS) from Integrated Public Use Microdata Series (IPUMS)-CPS of Minnesota Population Center. This survey data is collected through the monthly household surveys conducted by U.S. Census Bureau and Bureau of Labor Statistics (BLS). The data is collected for 1980-2008. Below, we describe the steps to process the data set to compute the wages and average weeks of work. The numbers in the parenthesis refer to the codes in the sample.

- Any person below 16 years and above 66 years of age is dropped from the sample.
- EDUCREC variable contains information on educational attainment. Any person with missing educational attainment (99), no education (01) and not in universe (00) is dropped from the sample. We divide the sample into four educational categories: less than high school (< 7), high school graduate (7), some college (8) and college graduate (9).
- LABFORCE variable indicates whether the person in the sample was a part of the labor force in the preceding week or not. Anybody who was not a part of the labor force (0 and 1), is dropped from the sample.
- EMPSTAT indicates whether the person in the sample was working or unemployed. We retain those people who were at work (10), had a job but did not work last

week (12) and armed forces (13). These three groups are categorized as employed by IPUMS-CPS.

- INDCODE provides information on the industry in which the person was employed. For our analysis, industry codes between 200 to 500 were classified as Manufacturing sector and between 500 and 900 were classified as Service sector. The non-farm, non-mining private sector includes all the industries between 246 and 900.

- CLASSWKR indicates whether the person is employed in the private industry or government sector or self employed. We drop the self-employed from the sample. Since our exercise deals with manufacturing, private services and a combination of both, we only retain those workers who work in the private industry for wage and salary (22).

- WKSWORK1 variable reports the number of weeks the worker worked in the preceding year. We assume anybody working less than 40 weeks a year is not a full time employee. So, we drop all the workers with less than 40 weeks of work.

- UHRSWORK variable provides information on the number of hours per week that the worker usually worked if they worked during the previous year. As per IPUMS-CPS, a person is categorized as a full time worker if he has worked 35 hours per week or more. So, we drop those respondents who have worked less than 35 hours per week.

- INCWAGE variable provides information on pre tax wage and salary income in the previous year. We use this variable to construct our variable on wage. Any person with code 999999 (Not in Universe), 999998 (Missing information) and zero income is dropped from the sample.

- Our measure on Average Labor Productivity (ALP) is RGDP per weeks worked. Though BEA provides information on total employed persons. The information on weeks worked is not available. We calculate the mean weeks worked for a sector "i" and "s" from the IPUMS-CPS processed data. While calculating the mean weeks worked, each person is weighted by the sampling weight variable “PERWT”. The “WKSWORK1” variable refers to the numbers of week worked in the preceding year. So, we forward the time one year ahead to arrive at the average weeks worked for the current year.

- To calculate the mean weekly wage for each labor group, we calculate the total weeks worked and total income wage by summing over all the individuals for that group for sector “i” and state “s” every year. While computing the total weeks worked and total income wage, we apply the sample weight “PERWT” to each person. Mean weekly wage for each group is calculated by dividing the total income wage by the total weeks worked. This mean wage is forwarded one time period ahead as the information on wage income belongs to the previous calendar year.
- The nominal weekly wage is deflated using the state-sector specific SGDP deflators.
- The real wage growth for a sector is calculated by weighting the real wage growth of each group by their labor income share. The labor income share is calculated by dividing the total income of the group by the total income of the sector.

Vita

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